



Technological University Dublin
ARROW@TU Dublin

Dissertations

School of Computing

2017

The Influence of Sensor-Based Intelligent Traffic Light Control On Traffic Flow In Dublin

Katja Rademacher
Technological University Dublin

Follow this and additional works at: <https://arrow.tudublin.ie/scschcomdis>

 Part of the [Computer Engineering Commons](#)

Recommended Citation

Rademacher, K. (2017) *The Influence of Sensor-Based Intelligent Traffic Light Control On Traffic Flow In Dublin*. Masters dissertation, Technological University Dublin, 2017. doi:10.21427/D7J89B

This Dissertation is brought to you for free and open access by the School of Computing at ARROW@TU Dublin. It has been accepted for inclusion in Dissertations by an authorized administrator of ARROW@TU Dublin. For more information, please contact yvonne.desmond@tudublin.ie, arrow.admin@tudublin.ie, brian.widdis@tudublin.ie.



This work is licensed under a [Creative Commons Attribution-Noncommercial-Share Alike 3.0 License](#)



The Influence of Sensor-Based Intelligent Traffic Light Control On Traffic Flow In Dublin



Katja Rademacher

D14128714

A dissertation submitted in partial fulfilment of the requirements of
Dublin Institute of Technology for the degree of
M.Sc. in Computing (Advanced Software Development)

2017

I certify that this dissertation which I now submit for examination for the award of MSc in Computing (Advanced Software Development), is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

This dissertation was prepared according to the regulations for postgraduate study of the Dublin Institute of Technology and has not been submitted in whole or part for an award in any other Institute or University.

The work reported on in this dissertation conforms to the principles and requirements of the Institute's guidelines for ethics in research.

Signed: Katja Redauecher

Date: **26 January 2017**

ABSTRACT

With growing cities and the increased use of vehicles for transportation purposes, there is a demand to make the traffic management in cities smarter. An intelligent traffic light control that dynamically adapts to the existing traffic conditions can help reduce traffic congestion and CO2 emissions.

This thesis reviews the popular traffic light control approaches - static, actuated and adaptive – based on their influences on recorded traffic conditions in Dublin. The Irish capital relies heavily on busses for public transport adding to the number of already moving vehicles in the city centre. Using vehicle count data from inductive loop detectors installed at the stop lines of numerous intersections in Dublin, the comparison and its results can be applied to the real world. Moreover, rainfall data is added to the dataset to provide insight into the influence of rainfall on the traffic conditions in Dublin. The findings reveal noteworthy differences in the daily volume development for the day categories weekday, weekend and public holiday.

The proposed adaptive traffic light control algorithm based on inductive loop sensor technology has the main intent of simplifying the traffic light program and providing a truly adaptive scheduling approach, while minimising the cost of implementing and integrating different kinds of sensor technology at the same time.

The results of the comparison indicate that the adaptive algorithm provides the shortest waiting times and highest average vehicle speeds compared with static and actuated traffic lights across all approaching vehicle volume levels. The adaptive approach also presents to be the best solution for varying traffic conditions of rapidly increasing or decreasing traffic volumes for every day as found in the input analysis. An adaptively controlled traffic light system outperforms the static and actuated approaches in the generated average waiting time by 41% and 17%, respectively.

Key words: *Intelligent Transportation System, Intelligent Traffic Lights, Adaptive Traffic Light Algorithm, Inductive Loops, Dublin, SUMO*

ACKNOWLEDGEMENTS

I would like to express my sincere thanks to my supervisor, Brendan Tierney, for his guidance and feedback throughout my thesis. His knowledge and patience was of great help.

I am also extremely grateful for the knowledge and help along with feedback from Aaron O'Connor from the Dublin City Council. He provided information on the existing traffic management in Dublin and helped with the selection of intersection for the analysis.

I would like to thank Annika Lindh, Thomas Bringewald and Diane Quirke for the support and valuable feedback on the written thesis.

Finally, a special thank you to my parents and sister for their support and love, along with beneficial feedback on the written thesis. They inspired my interest for technology and Computer Science and supported my decision for a postgraduate degree at the Dublin Institute of Technology in Ireland.

TABLE OF CONTENTS

1	INTRODUCTION.....	1
1.1	Background.....	1
1.2	Research Project.....	2
1.3	Research Objectives	3
1.4	Research Methodologies	4
1.5	Scope and Limitations.....	4
1.6	Document Outline	5
2	LITERATURE REVIEW AND RELATED WORK.....	6
2.1	Overview	6
2.2	Dublin City Council (DCC)	6
2.3	Traffic Control Management Systems	7
2.3.1	Definition	7
2.3.2	Existing Traffic Management Systems	7
2.3.3	Intelligent Transportation Systems.....	8
2.4	Intelligent Traffic Lights	9
2.4.1	Definition	9
2.4.2	Sensor Technologies.....	10
2.4.3	System Approaches.....	12
2.4.4	ITL Algorithms	14
2.5	Simulation of Traffic Light Control	16
2.5.1	Introduction.....	16
2.5.2	Software Tools.....	16
2.6	Summary	17
3	DESIGN.....	19
3.1	Overview	19
3.2	Input Data	19
3.2.1	Dublin City Council Data.....	19
3.2.2	Data Preparation and Storage	22
3.2.3	Initial Data Analysis	23
3.3	Experiments	28
3.3.1	Description.....	28
3.3.2	Simulated Traffic Light Control	30

3.3.3	Evaluation Measures of TLC Simulations.....	33
3.4	Adaptive Traffic Light Algorithm	34
3.4.1	Concept and Overview	34
3.4.2	The Definition of the Adaptive TLC Algorithm	35
3.4.3	Analysis of the Characteristics	39
3.5	Simulation Automation Software	41
4	EXPERIMENTS AND RESULTS.....	45
4.1	Overview	45
4.2	Evaluation of Input Data	45
4.3	Experiment 1: Vehicle Volumes.....	47
4.3.1	Overview	47
4.3.2	Results	48
4.4	Experiment 2: Consistent Traffic Conditions over the time span of one hour	52
4.4.1	Overview	52
4.4.2	Results	53
4.5	Experiment 3: Variable Traffic Conditions over the timespan of one hour	56
4.5.1	Overview	56
4.5.2	Results	57
4.6	Experiment 4: Day Simulations	59
4.6.1	Overview	59
4.6.2	Results	59
4.7	Summary	61
5	DISCUSSION	64
5.1	Overview	64
5.2	Use of Input Data.....	64
5.3	Adaptive Traffic Light Control.....	65
5.4	Results	67
5.4.1	Hypotheses.....	67
5.4.2	Comparison with current State-of-the-Art Results	69
5.5	Summary	71
6	CONCLUSION.....	73
6.1	Research Overview.....	73
6.2	Problem Definition	73

6.3	Design, Experiments and Results.....	74
6.3.1	Design.....	74
6.3.2	Experiments.....	74
6.3.3	Results and Evaluation.....	75
6.4	Contributions and Impact	76
6.5	Future Work.....	76
6.5.1	Extending Input Data Volume.....	76
6.5.2	Fine-tuning the Adaptive Traffic Light Control Algorithm	77
6.5.3	Experiments on a large Scale.....	78
	BIBLIOGRAPHY	79

TABLE OF FIGURES

Figure 3.1 Map of selected intersections and their positions in Dublin (Google Maps)	20
Figure 3.2 Detailed Google Maps satellite images from selected intersections from Dublin City (from left: Donore Avenue/South Circular Road, Talbot St/Lower Gardiner St and Sean Mac Dermott St/Lower Gardiner St)	21
Figure 3.3 DCC rainfall measurement mechanism.....	22
Figure 3.4 Monthly throughput for intersections.....	23
Figure 3.5 Average throughput per intersection for specific days.....	25
Figure 3.6 Daily rainfall for January - June 2016.....	26
Figure 3.7 Average intersection throughput for weekdays with rainfall information ..	26
Figure 3.8 Average intersection throughput for weekends.....	27
Figure 3.9 Average intersection throughput for holidays.....	27
Figure 3.10 SUMO networks for the intersections in Dublin (from left: Donore Avenue/South Circular Road, Talbot St/Lower Gardiner St and Sean Mac Dermott St/Lower Gardiner St).....	29
Figure 3.11 2-phase system for the adaptive TLC algorithm – EW-direction and NS- direction.....	35
Figure 3.12 Main path of the adaptive TLC algorithm.....	36
Figure 3.13 Rules for the next phase determination	37
Figure 3.14 Rules for the calculation of the phase length	38
Figure 3.15 Waiting times for edges (period: 60 seconds) for the algorithm forms	39
Figure 3.16 Detailed view of the waiting times for edges (period: 60 secs)	40
Figure 3.17 UI for the Simulation Automation Tool.....	42
Figure 4.1 Comparison between input and output loop data converted to average intersection throughput on rainy weekdays.....	46
Figure 4.2 Comparison between input and output loop data converted to average intersection throughput on holidays	46
Figure 4.3 Comparison between input and output loop data converted to average intersection throughput on weekends	47
Figure 4.4 Development of average waiting time for each intersection based on the vehicle volume	48

Figure 4.5 Average waiting times based on TLC for increasing vehicle volumes.....	49
Figure 4.6 Average speed per vehicle for increasing vehicle volumes	50
Figure 4.7 Average travel time for all vehicle volume levels.....	51
Figure 4.8 Average length of green light phases for the increasing vehicle volumes..	51
Figure 4.9 Maximum length for the green light phases for actuated and adaptive TLCs	52
Figure 4.10 Average waiting time for consistent traffic conditions	54
Figure 4.11 Average travel time for consistent traffic conditions	55
Figure 4.12 Average green phase duration for consistent traffic conditions	55
Figure 4.13 Average waiting time for variable traffic conditions	57
Figure 4.14 Average travel time for variable traffic conditions	57
Figure 4.15 Average duration of green light phases for variable traffic conditions.....	58
Figure 4.16 Average waiting time for the defined day categories weekdays, weekends and holidays.....	59
Figure 4.17 Average travel time for defined day categories weekdays, weekends and holidays	60
Figure 4.18 Average green light phase duration for defined day categories weekdays, weekends and holidays.....	61
Figure 4.19 Overall average duration of green phases for an intersection in Dublin...	62
Figure 4.20 Average waiting time for TLC approaches in Dublin.....	63

TABLE OF TABLES

Table 3.1 Relevant state holidays of Republic of Ireland for 2016 for the input data
from DCC 24

Table 3.2 Static traffic light program 31

Table 3.3 Actuated traffic light program 32

Table 3.4 Adaptive traffic light program 35

Table 4.1 Average volume for the categories of variable traffic conditions 56

1 INTRODUCTION

1.1 Background

Nowadays more than 75% of the population in Europe lives in urban areas¹. More people are travelling to work, into the city or across the city to get to the important locations of their lives. This causes more traffic and congestion.

With the evolution of technology in the last 20 years and the amount of people living in a more densely populated area the need arises to evolve the existing cities into so-called ‘smart cities’. Smart cities can be defined as energy-efficient, intelligent and environment-friendly cities. They offer the possibility to use existing technology to make the cities on this planet a more advanced and attractive place to live in².

Research in the area of smart cities has become increasingly important in recent years. LazaroIU and Roscia (2012) describe a smart city model with six key fields that sum up a smart city. These fields are Smart Living, Smart Economy, Smart People, Smart Governance, Smart Mobility and Smart Environment. The two main fields applicable for this project are Smart Mobility and Smart Environment. The main goals of Smart Mobility are local accessibility and innovative and safe transport systems. Reducing pollution and creating a sustainable resource management are points that fall in the field Smart Environment (LazaroIU & Roscia, 2012).

Traffic congestion and variable traffic conditions are problems of existing cities. The idea of smart cities has set its goal to solve these problems. Reducing traffic density not only has an impact on road safety but also lowers CO2 emissions in cities (Djahel, Doolan, Muntean, & Murphy, 2015).

Smart or dynamic traffic lights have been a centre for research with regard to adjusting their settings to the demand presented by vehicles in a city. The idea is to change the traffic lights based on the traffic conditions to enhance efficiency of intersection throughput and reduce pollution (Miz & Hahanov, 2014; Mohamed, Abderrahim, Anouar, Mohammed, & Kaoutar, 2015).

¹ Based on the information from the Smart cities initiative of the European Commission: https://eu-smartcities.eu/about/european_context (Retrieved on 12.11.2016)

² Based on the information from the Smart cities initiative of the European Commission: https://eu-smartcities.eu/about/european_context (Retrieved on 12.11.2016)

The Irish city of Dublin, as one of the capitals in Europe, has 1.2 million citizens and relies heavily on road traffic. This not only includes the private vehicles but also public transport with 1000 buses travelling around Dublin on a daily basis. The Dublin City Council (DCC) possesses a department specifically for the traffic management in the city area. They use CCTV and inductive loop sensor technology to measure and manage the traffic conditions in their operation centre. Additionally, management software is used to coordinate the traffic lights and their scheduling for automation purposes (IBM, 2013; O'Connor, 2016a; Suzumura, McArdle, & Kanezashi, 2015).

1.2 Research Project

This project aims to combine the research into smarter traffic lights with the existing traffic conditions of Dublin. This includes an analysis of different traffic light control approaches and their influence on the experience for vehicles approaching an intersection in Dublin.

To make the management of traffic lights smarter, the use of sensor technology for detecting the existing traffic conditions proves to be very successful. While there are several sensor technologies available, many of them are futuristic. Another option is the use of inductive loop sensors that are already used by the installed traffic management software at the Dublin City Council. This alternative approach can be seen as intelligent traffic light control based on inductive loops and algorithms to determine the traffic light dynamically in real-time.

Current traffic light management systems are based on one of the three main scheduling techniques: static/fixed-time, actuated or adaptive. Based on this fact, the research question this thesis aims to solve is as follows:

How does a sensor-based Intelligent Traffic Light Management System influence traffic flow in Dublin compared to static and actuated traffic light scheduling?

This intelligent traffic light management system uses an adaptive traffic light control algorithm to manage the traffic lights based on the approaching traffic conditions. A traffic light scheduling algorithm is proposed in this project with a focus on simplicity and effectiveness. Thus, the null hypothesis uses the overall comparison of the traffic light control approaches as its foundation:

Hypothesis 0: The proposed adaptive traffic light algorithm can handle the approaching traffic conditions better than static and actuated traffic light scheduling.

Moreover, three additional hypotheses are created based on the traffic flow and traffic light variables that are used in the analysis of the results for the comparison between the traffic light control strategies. The first variable is the average speed of vehicles approaching an intersection.

Hypothesis 1: The average speed of approaching vehicles falls with increasing traffic volume levels.

The traffic volume does not only impact the average vehicle speed but also the waiting and travel times of vehicles as the other two variables associated with traffic flow. This is the content of the second hypothesis.

Hypothesis 2: The waiting and travel times for approaching vehicles rise with increasing traffic volume levels.

The last hypothesis is based on the duration of green light phases set by the traffic light controller and its influence on the waiting time for vehicles.

Hypothesis 3: Shorter green light phase durations produce shorter waiting times.

Data from the Dublin City Council is used to evaluate the hypotheses in the conducted experiments with regard to the established research question.

1.3 Research Objectives

The objective of the research is to show that an intersection controlled by sensor-based, intelligent traffic lights can increase the traffic flow in Dublin city centre compared to static and actuated traffic light scheduling. Moreover, an adaptive traffic light control is proposed that can dynamically change the duration of allowed green times for the controlled intersection based on the number of approaching vehicles. These are detected by inductive loop sensors installed in the roads. Rainfall and vehicle count data is analysed providing insight into the caused intersection throughput for a day with regard to its characteristic features. Individual intersections are created in the road traffic simulator Simulation of Urban Mobility (SUMO) and input data from the Dublin City Council on traffic volumes and rainfall is transformed to run the simulations. The results are compared based on the waiting times, travel times, vehicle

speed and green phase duration generated by the different traffic light controller categories static, actuated and adaptive.

1.4 Research Methodologies

Secondary research will be conducted for the project in the form of a literary research and review. This will consider detailed information on traffic light management systems, the comparison of sensors, traffic light management approaches and the predominantly used software tools for traffic light simulations. Further research on similar projects and the used simulation tool SUMO is performed for the comparison of results to similar projects and needed information on the implementation of the proposed traffic light control algorithm.

The primary research is applied during the analysis and experiments to be conducted within this thesis. The analysis of input data and results from the experiments is quantitative because variables such as throughput, waiting time and green light phase durations are measured and compared by their value. This includes the vehicle count data and rainfall data retrieved from the DCC and the output data from the simulations embedded in the experiments.

Moreover, the adaptive traffic light control algorithm is designed based on the acquired knowledge found in the literary research. It is implemented using Python script language and an application programming interface (API) from SUMO to interact with the simulation.

1.5 Scope and Limitations

The main intention of this thesis is the comparison between the static, actuated and adaptive traffic light control with existing traffic conditions from the city centre of Dublin. The adaptive approach is based on a designed algorithm that uses detector data for the description of the existing vehicle volumes at an intersection. The data used for the simulation is the detected vehicle counts from installed sensors at three intersections in Dublin over a six-month period. Using these intersections the simulation foundation is prepared to run with user-selected data from the available data range. The results of the experiments are to be analysed based on the traffic flow variables and the traffic light information on the phase durations that can be provided by the simulation tool.

The traffic light control approaches are only tested and compared on the individual intersections. Due to the limited time, experiments on a whole network or adjoining junctions cannot be run.

1.6 Document Outline

The following chapter reviews the existing research on current and intelligent traffic management software, approaches and sensor technology used for the design of intelligent traffic light control with a focal point on algorithms and finally the available simulation tools.

The design of the input analysis and the experiments with its evaluation measures are described in chapter 3. Here, the proposed adaptive traffic light approach is also illustrated with details on the algorithm and the sensors used for vehicle detection.

Following the design of the experimental environment, the specific experiments for the comparison of the traffic light approaches are portrayed with their generated results.

Chapter 5 discusses the design, experiments and results with regard to the research question, the hypotheses and current research.

The last section is the conclusion with details on the impact of this thesis and future work.

2 LITERATURE REVIEW AND RELATED WORK

2.1 Overview

This chapter aims to define the existing literature in the area of transportation systems and traffic control approaches. Given that the project layout for the data and experiments is Dublin city, the first section will go into detail on the work done by the Dublin City Council and the existing Transport Management Systems. Based on that knowledge, the state of the art approaches in Intelligent Traffic Light Control systems with sensor technologies and algorithms are described. The last section covers the literature on simulation tools used for testing traffic conditions and traffic light control algorithms.

2.2 Dublin City Council (DCC)

The Dublin City Council has a traffic management department to control the road network and traffic situation in the city centre of Dublin. Not only does it use a traffic management system called SCATS (see chapter 2.3.2), but it has an operation control centre to respond to traffic situations in real-time. The operators use CCTV cameras and the SCAT system to change the traffic light controls at specific intersections on demand. DCC collects several kinds of data including information on traffic volume in the context of vehicle counts and road journey data (O'Connor, 2016a).

Because of its different departments, they also provide data in several other aspects including weather data. The data that is of interest for research in the traffic management area is the rainfall statistics and its influence on traffic conditions in Dublin throughout the day (O'Connor, 2016a).

Over the last years, DCC and IBM have teamed up to create a more advanced traffic management system by using various kinds of data sources including real time updates from CCTV cameras positioned at the intersections, bus position and social media data from Twitter or SMS messages (Daly, Lecue, & Bicer, 2013; O'Connor, 2016a).

2.3 Traffic Control Management Systems

2.3.1 Definition

Traffic Control Management Systems or more commonly named Urban Traffic Control (UTC) systems have the purpose to optimise road traffic in a city using the method of controlling traffic lights. UTC systems have been around for the last fifty years helping cities with their traffic management. They result in a large improvement of the traffic flow through a city when installed (Robertson & Bretherton, 1991). Important control variables that are used within a traffic control management system are phase, cycle length, split plan and offset. A phase is the amount of traffic movements that are allowed to cross the intersection at the same time. Cycle length is the time needed to complete a full cycle of all given phases for the intersection. The split plan defines the percentage each phase gets within one full cycle. The parameter offset is used to create a flow of traffic across multiple intersections. This means that the waiting time and amount of stops can be reduced with this setting (Wongpiromsarn, Uthaicharoenpong, Wang, Frazzoli, & Wang, 2012).

In the following two sections the existing traffic management systems is discussed in further detail and an introduction to the idea of an Intelligent Transportation System (ITS) is given.

2.3.2 Existing Traffic Management Systems

There are several adaptive Traffic Management Systems that exist in the traffic management of cities, with the two most popular being the Split Cycle Offset Optimisation Technique (SCOOT) and Sydney Coordinated Adaptive Traffic System (SCATS). Both systems have been around for the last twenty to forty years and are installed in various cities around the world (Robertson & Bretherton, 1991). They are still state-of-the-art solutions for traffic management in cities but have become more advanced with the introduction of new technology and sensors.

Both systems rely heavily on inductive loops positioned in the lanes of the given approaching roads. The data from inductive loops can give information on whether a car is positioned at the stop line and how many cars cross the loop and therefore enter the intersection on a given lane.

Not only is SCOOT a popular traffic light management system, it is also used by Traffic Solutions Ltd. to control the traffic lights in the outer areas of Dublin City (McGoldrick, 2016). Its key ideas are real time measurement of cyclic flows, updating the online model of existing queues and optimising the settings of the traffic lights incrementally (Robertson & Bretherton, 1991). The SCOOT system provides the functionalities of prioritising busses at a traffic light and a procedure called ‘gating’. The bus priority allows the system to skip stages for approaching busses if needed and useful. Upon a detection of a bus, the system can conclude that the changing of the traditional cycle to accommodate the bus is helpful. While this decreases the delay for busses passing the intersection, it increases the delay for the other vehicles (Bretherton, Bodger, & Baber, 2004). Gating allows the limitation of traffic into a specific area to reduce the traffic flow. This means that traffic congestion and queues can be relocated to an area where they are less problematic (Bretherton et al., 2004; McGoldrick, 2016). The SCATS system aims to maximise the percentage of effectively used time of vehicles passing the intersection compared to the total green light time as the most common cause for waiting times and stops is the traffic light setting. This results in the need to optimise the split plan and cycle length of an intersection. Cycle length and the split plan are two of the parameters needed for the configuration of each intersection in the network covered by SCATS (Wongpiromsarn et al., 2012). The advantages of using SCATS in a city are decreasing travel time, the number of accidents and fuel consumption. These advantages then result in a less polluted city because of the increased throughput and less travel time for vehicles within the given area (Sims & Dobinson, 1980). The SCATS system is used by the DCC to manage traffic flow in Dublin City.

2.3.3 Intelligent Transportation Systems

While the traffic systems SCOOT and SCATS are existing traffic management control systems installed in numerous cities, the Intelligent Transportation Systems (ITS) is the ideal and ultimate goal for the management of transportation in a city and a big aspect in the research and development in this area. An ITS can solve the problems of Smart Mobility and Smart Environment that present aspects of the future smart city. ITSs aim to make transport in a city more efficient and reliable for consumers. This goal can be further refined with aspects of improving road safety, the optimisation of

traffic flow and its speed and thus reducing the energy consumption caused by various means of transportation to a minimum (Tubaishat, Shang, & Shi, 2007).

With the introduction of Big Data and the advancing technology for sensors, the impulse for a data-driven ITS is born. It is based on the idea that data from multiple sources is used to create a more intelligent system that manages the transport and traffic through a city in real time. This data is heterogeneous as it comes from various kinds of sensors installed in the set area to provide an overview of the system state. This poses a problem of handling and integrating all incoming data that vary in format, velocity and volume in real time (Lécué et al., 2014). Additionally, the amount of data has to be processed and analysed by the ITS to create traffic models that manage the traffic and transport flows. ITSs are often based on one or more reasoning techniques. These include Description Logic, rule-based and machine-learning based reasoning (Lécué et al., 2014). Multiple parties involved into the development of an ITS create a challenge for the implementation of an ITS (Gasparini et al., 2011). Companies like IBM and Dublin Bus and institutions such as the Dublin City Council are involved in the development of a more intelligent traffic control system in Dublin city (Daly et al., 2013).

An ITS can be separated into four subsystems: surveillance system, communication system, energy efficiency system and traffic light control system (Tubaishat et al., 2007). The latter element is the area of interest for this project. The following section goes into more detail for traffic light control in the context of ITS.

2.4 Intelligent Traffic Lights

2.4.1 Definition

There are three different types of traffic lights: static, actuated and adaptive. The fixed-time or static traffic lights have a set time for phases and the split plan. Actuated traffic lights determine the phase length from a fixed cycle length and therefore the split plan is based dynamically on the approaching and existing traffic (Dotoli, Fanti, & Meloni, 2006). The last option is to use adaptive traffic lights for traffic control (B. Zhou, Cao, Zeng, & Wu, 2010). While the traffic light control with SCATS using inductive loops and other data sources are quite adaptive, intelligent traffic lights (ITL) are a more advanced version and goal of adaptive traffic lights. An ITL system focuses on the maximisation of safety on the roads and speed of traffic flow, while also minimising

waiting time, energy consumption and the number of stops that vehicles are required to have during their trip through the network. To achieve these goals, an ITL system has to consider the following variables for each intersection:

1. Intersection type: What type of intersection is it? How many lanes does it include?
2. Traffic volume: The traffic volume has to be estimated and calculated to adapt the traffic lights. The volume of approaching vehicles can change fast and that needs to be considered.
3. Time of day: Depending on the time of the day there might be different cycle times needed.
4. Effects on other roads: With the varying green phase times at one intersection, the traffic flow approaching the adjoining intersections is changed.
5. Pedestrian traffic: Depending on the time of the day there might be a lot of pedestrians wanting to cross the street or none (B. Zhou et al., 2010).

With a set definition for ITLs, the next sections discuss different setups and technologies involved in providing a successful ITL system.

2.4.2 Sensor Technologies

Data aggregation is a crucial element to an intelligent control system, as it needs to know as much of its environment as possible to be able to control it successfully. Existing and future sensor technologies solve this problem by having the ability to convert a physical measure into an electronic signal. Information measured by sensors includes light, pressure, temperature and magneto-strictive data. With various types of sensors collecting data on traffic conditions, air pollution and environmental noise among others, there is a need for a powerful communication strategy and a robust data aggregation and integration design. The first is necessary to provide a fast and reliable connection between the sensors and the control unit (Hancke, Silva, & Hancke, 2012). The second need is based on the challenges of redundant data and correlating information from the different sources (Djahel, Doolan, et al., 2015).

There are several approaches in this area that cater to the need of reliable communication while trying to keep the cost to a minimum and the communication strong. The most popular options are the Internet of Things, Wireless Sensor Networks (WSN) and Cloud of Things. The Internet of Things and Cloud of Things rely more

heavily on cables, when connecting the sensors and either their own system or the cloud for storage and integration of data. Wireless Sensor Networks on the other hand solve the communication issue by connecting the sensors with each other using solely wireless networks. With the development of using more and more sensors in areas, cables for every installed device can become impractical and expensive. In WSNs the data is sent across multiple sensors until it reaches its destination (Hancke et al., 2012). Vehicular Ad Hoc Networks (VANETs) present a form of WSN-based technology to measure traffic conditions. The premise is that vehicles communicate with each other via vehicle-to-vehicle (V2V) communication and with traffic lights via vehicle-to-infrastructure (V2I) communication. Based on received information from vehicles, traffic lights can be changed dynamically. This can be achieved by vehicles sending messages with information regarding the number of immediate vehicles surrounding them (Barba, Mateos, Soto, Mezher, & Igartua, 2012). This technology could be useful in smart cities in the future, but is not feasible as of yet. According to Djahel, Doolan, et al. (2015) the technology will become more important and available in the next couple of years.

The use of sensors in an ITL system can provide a more thorough estimation of the existing traffic condition that in turn builds the foundation for the adaptive traffic lights. Sensing used in an ITL system not only include physical sensors like inductive loops and video cameras, but also data from social media and vehicles with communication units. Examples for these vehicles are busses, taxis and emergency vehicles (Djahel, Doolan, et al., 2015).

Sensing information from social media platforms like Facebook and Twitter can add information on the cause of traffic conditions to the ITL systems. Existing sensors like camera sensors and inductive loops provide a general overview on the traffic volume, with video sensors having the advantage of discovering congestion causes like accidents or road works. There are other sources for traffic congestion that cannot be identified with these sensors. Examples for these are special events or holidays. A question that hinders the extensive use of every social media information is how reliable the information and source is. An idea to solve this is to create a reward system for trustworthy information, as proposed by Djahel, Doolan, et al. (2015) and limiting the sources within the social networks. The ITS project in Dublin only uses tweets

from certain certified sources to provide the security when handling traffic conditions (Daly et al., 2013).

Video sensors can provide visual evidence of a situation at the position of the camera. Originally used for surveillance systems, it has proved to be quite successful and an inexpensive solution for estimating traffic conditions. Not only can existing surveillance cameras be used for the tracking of traffic flow but they can be easily installed and the maintenance costs are low. The collected video data has to be used as input for algorithms detecting vehicles and estimating the traffic volume. A disadvantage of a camera sensor is that its data quality relies on lighting and weather conditions (Hancke et al., 2012).

Inductive loop sensors have the ability to record traffic data in a detecting interval as they are loop detectors buried in roads. When a car approaches the detector, the frequency in the loop is changed. The caused level of changes in frequency provides information on the size of the passing vehicle. Inductive loops provide good results, as most vehicles nowadays consist of ferrous metals (Dissanayake, Senanayake, Divarathne, & Samaranayake, 2009). Based on this information, the traffic volume and average speed of the approaching vehicles can be calculated and the information used to adapt the traffic lights if the distribution of loop detectors is high enough to define the existing traffic conditions (Guo, Jiang, & Zhu, 2007; Hancke et al., 2012).

2.4.3 System Approaches

Current approaches to control traffic lights are based on sensing in smart cities as described above (Tubaishat et al., 2007). This produced information can be seen as valuable input data for real-time traffic adjustments of an Intelligent Traffic Lights system. Similar to the Intelligent Transport System approaches, ITL systems rely heavily on decision-making techniques that include not only logic-based and machine-learning approaches, but also methods from other more established research areas, such as music or biology.

The primitive logic-based concept of ITL systems can be seen as solely logically based approaches with Prolog predicates to define situations and make decisions as described in the European INSIGHT project that also uses Dublin Traffic Data for its problem simulation (Artikis et al., 2014). The more advanced logical ITL systems use fuzzy logic or full expert system techniques with a knowledge base containing a set of rules

and an inference machine as reasoning layer to find optimal solutions (Keyarsalan & Ali Montazer, 2011; Wen, 2008).

While there are several types of the machine-learning techniques, there is one type worth mentioning in this context of highly dynamic traffic light management. The idea of Reinforcement Learning is the ability of detecting pattern changes and relearning when interacting with its surrounding environment (Salkham & Cahill, 2010).

Biological concepts that are adopted for ITL system designs are Swarm Intelligence and Genetic Algorithms. Both ideas have the common element that is a fitness function. Swarm intelligence is an intelligent paradigm that is based on the biological concept of swarming and flocking. This includes the Particle Swarm Optimisation technique that can be used to solve problems in traffic management and schedule traffic lights dynamically in real time (Hu, Wang, Yan, & Du, 2015; Rakkesh, Weerasinghe, & Ranasinghe, 2015).

Fujdiak et al. (2015) provide a description of an intelligent traffic light management system based on a genetic algorithm. Genetic algorithms try to describe “the natural process of evolution and multiplication” (Fujdiak, Misurec, Mlynek, & Petrak, 2015).

Moreover, a concept from music theory is used to advance the management of traffic light control. The discrete harmony search algorithm is motivated by the process of finding the optimal harmony for a musical performance and sets the optimal set of traffic light stages for a road network equal to a perfect harmony (Gao, Zhang, Sadollah, & Su, 2016).

Zhou, Bouyekhf and EL Moudni (2013) use the similarities between flowing energies in thermodynamic systems and vehicles in a road network to create a model for traffic light management with the individual roads presenting the subsystems of a thermodynamic system. While the directions and flow volumes of energies in a thermodynamic system can be calculated based on the existing temperatures in the adjoining subsystems, the directions of vehicles rely on the decisions of the driver and the quantities of vehicles passing an intersection in a specified time period depends on the traffic light control.

Finally, the GLOSA system (Bodenheimer, Eckhoff, & German, 2015) uses the petri-nets and graph theory to define the methods for its traffic management concept.

An important aspect of the design of an ITL system is also the architecture and the decision on a centralised versus distributed management approach. The centralised

system with one optimisation solver provides a more homogenous solution to the traffic management problem but managing a large network of traffic lights in real-time dynamically is nearly impossible as the tests from Zhang and Gao (2015) show. They also present a solution to the scalability challenge by dividing the network into smaller regions with a set number of intersections that are managed by individual controllers. Another option is to implement a controller for each intersection (Wongpiromsarn et al., 2012). This can be realised by the concept of multi-agent systems that do not rely on a central control system but make decisions based on the documented traffic situation at the specific intersection. While the agents act independently, collaboration between neighbouring agents advances the traffic control (Salkham & Cahill, 2010; Yu, Wu, & Yang, 2016).

2.4.4 ITL Algorithms

The important responsibility of all ITL algorithms is to determine the traffic light scheduling factors green light durations, phase sequence and the full cycle time. According to Younes and Boukerche (2016), ITL algorithms are more efficient, the shorter the cycle time is. This is based on the argument that less cars are waiting at an intersection, the shorter the cycle is, while also allowing enough vehicle to pass (Younes & Boukerche, 2016; Younis & Moayeri, 2016). A cycle can be calculated from the sum of green phase durations and the amber transition times between the phases. These transition times are often set to a specific duration and present a safety measure between the phases to prevent accidents (Al-Khateeb & Johari, 2008). The cycle time can be fixed (Dotoli et al., 2006; Suthaputchakun & Sun, 2015) or dynamically set based on the phase durations (Wen, 2008; B. Zhou et al., 2010).

An intersection can have multiple phases for the allowed movements of crossing vehicles with two phases and four phases being the most popular occurrences for traffic light control management at a simple two-way intersection. The two-phase system symbolises the idea of north-south- and east-west-bound traffic being individual phases. Four-phase systems can either mean that each direction has its own phase or the two-phase system is extended with the phases for crossing vehicles that would be hindered by the simple two-phase system. These vehicles want to turn right in a left-hand traffic or turn left in a right-side traffic system (Al-Khateeb & Johari, 2008; Li, Zhang, & Chen, 2016; Möller, Fidencio, Cota, Jehle, & Vakilzadian, 2015).

As the green light phase durations influence the cycle time and the throughput of an intersection, this is a problem that every ITL algorithm tries to solve. Some approaches set maximum and minimum durations as reference times for the calculation (Kanungo, Sharma, & Singla, 2014; Li et al., 2016). This is to avoid too many switches and long waiting periods. Input data for the calculation and decision on phase duration can be vehicle speeds, average queue lengths, the traffic density and vehicle counts.

Möller, Fidencio, Cota, Jehle and Vakilzadian (2015) propose a cyber-physical system for intelligent traffic light control where the distances and speeds of approaching cars determine the green light time of the traffic lights. This is based on the idea that the traffic light should be green, once the vehicle reaches the intersection. The average speed of approaching vehicles can determine the existing traffic situation.

The lengths of waiting vehicle queues at intersections are the basis for several ITL algorithms. The TRANSYT method (Robertson & Bretherton, 1991), backpressure routing algorithm (Wongpiromsarn et al., 2012) and RED approach (Alabdallaoui, Berraisoul, & Idboufker, 2015) among others use the queue length to determine the phase duration. Random Early Detection (RED) compares the average queue size to two thresholds to define the traffic situation and schedule the traffic lights dynamically. Traffic density and vehicle volume can be parameters for ITL algorithms (Mohamed et al., 2015; Younes, Boukerche, & Mammeri, 2016; Younes & Boukerche, 2016).

The phase sequence needs to be determined to finish the scheduling of a traffic light. With the given input data, if a given value is zero the phase can be skipped to save time in the cycle as the phase is not needed (Covell, Baluja, & Sukthankar, 2015; Younes & Boukerche, 2016). Whether the sequence is cyclic as in NESW or based on certain circumstances, the sequence has to be set. The on-line algorithm sets its phase sequence based on the arrival time of vehicles and the concept of first come first serve whereas other algorithms schedule the phase with highest densities or longest queues first (Wongpiromsarn et al., 2012; Younes et al., 2016; Younes & Boukerche, 2016; B. Zhou et al., 2010).

Li et al. (2016) not only propose an adaptive traffic light algorithm but also compare this control mechanism to static and actuated traffic lights, as these three approaches are most common in current traffic management systems.

2.5 Simulation of Traffic Light Control

2.5.1 Introduction

Simulation offers the approach of testing ideas in a controlled environment without having to rely on existing infrastructure. This means the theories in research can be tested before implementing them in the real world. In case of ITS and more specifically ITL, the performance and results of applications and algorithms can be tested without the need for existing functionality with regard to used technology and the cost of resources.

There are two types of traffic modelling and simulation techniques. Macro simulators focus on models of traffic flows without detailed information on vehicles. The model provides a simulation and model of traffic flow from a high level aspect. The micro simulators go into more detail information and regard individual vehicles as important factors of a traffic system (Djahel, Doolan, et al., 2015).

2.5.2 Software Tools

Within in the applications of ITL systems the micro simulators are mostly used to test the developed ideas, as they provide detailed information on the traffic volume and approaching vehicles.

Simulation of Urban Mobility (SUMO) is the most popular micro simulator. It is an open-source traffic simulator that provides a various number of different features (Djahel, Doolan, et al., 2015; Mohamed et al., 2015; Rakkesh et al., 2015; Younes et al., 2016). The user can choose between different vehicle types, has the option to define multilane streets that support lane changing, select between various right-of-way rules and change the traffic light control or define its algorithm for the traffic lights. The software provides various outputs from the simulation and the option to run the simulation either in the background or on a graphical user interface (Djahel, Doolan, et al., 2015; Krajzewicz, Hertkorn, Rössel, & Wagner, 2002; Mohamed et al., 2015; Younes et al., 2016).

Based on SUMO and the Network Simulator 3 (NS3) is the simulator iTETRIS which stands for Integrated Wireless and Traffic Simulation Platform for Real-Time Road Traffic Management Solutions. iTETRIS presents the best performance for large-scale

simulations. It is most commonly used to test VANET applications with communications between vehicles and infrastructures (Djahel, Doolan, et al., 2015).

Simulating an ITL system, the Green Light District Simulator (GLD) presents an alternative to SUMO. It allows the comparison between various different existing traffic light control (TLC) mechanisms and the introduction of personal TLC algorithms (Srivastava & Sudarshan, 2013; Tubaishat, Qi, Shang, & Shi, 2008).

The last simulator that is used in the simulation of ITS and ITL is called VISSIM. It is a discrete event traffic simulation system that models motorway and urban road traffic and uses complex mathematical models for its simulation (Djahel, Doolan, et al., 2015; Köhler & Strehler, 2012).

Various research papers (Alabdallaoui et al., 2015; Li et al., 2016; Wongpiromsarn et al., 2012; Xiao, Xiao, Wang, & Li, 2015) use MATLAB to simulate their ITL algorithms, but it is not a specific simulator for road traffic conditions.

2.6 Summary

With new technology on the rise and the idea of wireless sensor networks and internet of things becoming extremely popular, there is a demand to advance the existing Traffic Control Management systems like SCATS or SCOOT into intelligent cyber-physical systems (Younis & Moayeri, 2016). Part of an ITS is the concept of Intelligent Traffic Lights. The research on sensor-based intelligent traffic lights is quite extensive. The literature has shown that there are various different approaches with sensor technologies and system designs, as shown above. In this case the idea is to not use an expert system, machine-learning technique or another logical reasoning approach to determine the traffic light schedule dynamically based on existing traffic conditions.

Therefore, the main element of the ITL system is an algorithm that has the same functionality. The ITL control algorithm sets out to define the parameters phase durations, phase sequence and cycle length in real-time by using different input data like queue length and traffic density. The algorithms can be tested in simulations to test the success rates of the defined algorithms. SUMO is the most popular simulator for road traffic situations with the ability to add traffic light algorithms and define the traffic volume using the input options. Thus, the decision is made in favour to this software tool to simulate and analyse the traffic conditions of Dublin city. While there

are several algorithms used to manage traffic conditions, there is no existing research using Dublin City data with a context of rainfall data and the comparison of fixed, actuated and adaptive traffic light controls.

How does a sensor-based Intelligent Traffic Light Management System influence traffic flow in Dublin compared to fixed and actuated traffic light scheduling in varying rainfall conditions?

3 DESIGN

3.1 Overview

The design of this research is described in this chapter detailing the input data, the experiments to be conducted, the used adaptive algorithm and tool used to run the simulations automatically. In the first step the range and use of data from the Dublin City Council with vehicle counts and rainfall data is explored with a focus on data preparation and the initial data analysis. Following this description is the design of the experiments with the simulations and the detailed setup of the static and actuated traffic light control approaches used within the experiments. The output options are discussed to define the measures for the analysis and comparison of the experimental results. An adaptive traffic light scheduling algorithm is proposed and described. The last section depicts the developed automation tool based on Qt to run the simulations of all three traffic light controls automatically.

3.2 Input Data

3.2.1 Dublin City Council Data

In the preliminary stages of this project an open dataset from the DCC was found that defines journey times across Dublin city and the roads the journey times are set for. There are 900 records for every minute a day, for all routes within Dublin. With at least thirty days of data there should be enough records to ensure the data is acceptable for preliminary analysis of influence of traffic light scheduling on traffic conditions within Dublin. This journey time data needs to be transformed in some way into the distinctive vehicle counts approaching the intersections to allow any kind of simulation with SUMO. This not only poses as a huge risk of not illustrating the given data in the right way but also a challenge of the right transformation procedure.

With the assistance from the DCC, an alternative dataset is chosen with traffic data of intersections in Dublin. This eliminates the transformation problem as described above. The DCC has data on vehicle counts for the inner city of Dublin. This is based on the circumstance that inductive loops are positioned in nearly every lane at the intersections in Dublin city. The traffic counts from these sensors can be used for this thesis and allow a more thorough analysis.

One record of the vehicle count dataset describes the number of cars that passed the inductive loop within a time span of 15 minutes. This means that for every detector there are 96 records per day.

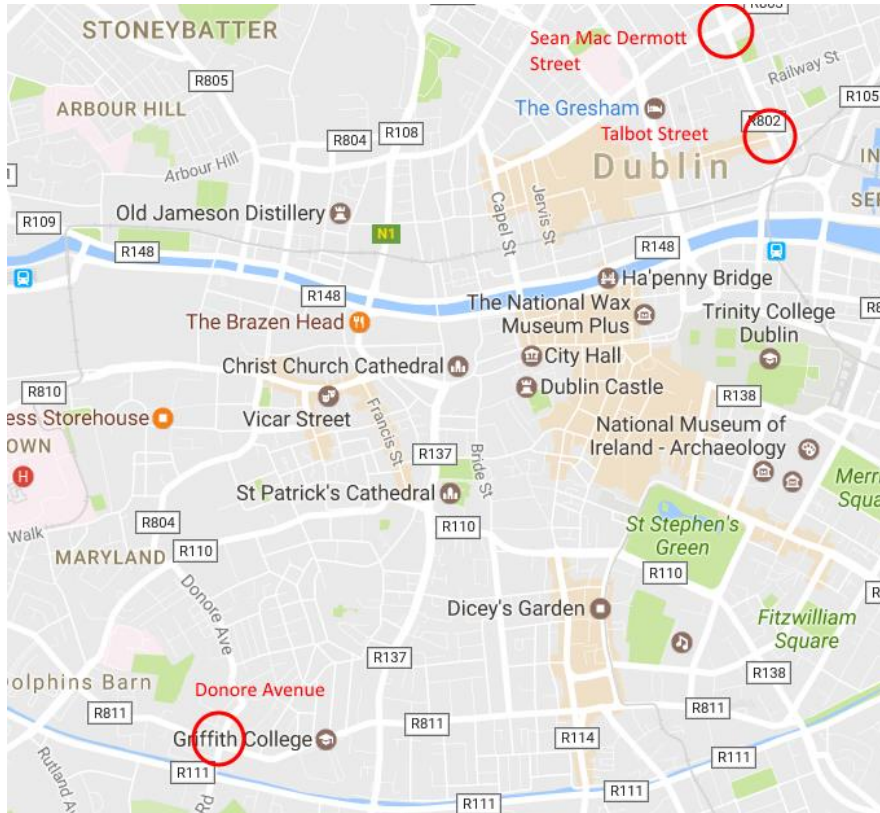


Figure 3.1 Map of selected intersections and their positions in Dublin (Google Maps)³

Three intersections in the city centre of Dublin, which have a complete dataset for the first six months of 2016, are chosen for this project. Over the set time span of six months there is a chance that one of the inductive loops might produce ‘BAD’ as its recorded data because of failures within the sensor (O’Connor, 2016a). These three intersections Donore Avenue, Talbot Street and Sean Mac Dermott Street have minimal missing data records and are therefore chosen in cooperation with the Dublin City Council (see Figure 3.1 and Figure 3.2). Figure 3.1 shows the general positions of the intersections in relation to the Dublin city centre, whereas Figure 3.2 displays the detailed satellite view of the intersections showing the approaching lanes and allowed directions in a matter of arrows carved into the road.

³ Google Maps: <https://www.google.de/maps/place/Dublin,+Ireland/@53.3383439,-6.2729405,14z/data=!4m5!3m4!1s0x48670e80ea27ac2f:0xa00c7a9973171a0!8m2!3d53.3498053!4d-6.2603097>

The vehicle count data from the DCC sets out to provide the basis for the final evaluation and the input for the simulation in the simulation stage. Therefore, the data is prepared with inconsistent data being removed.

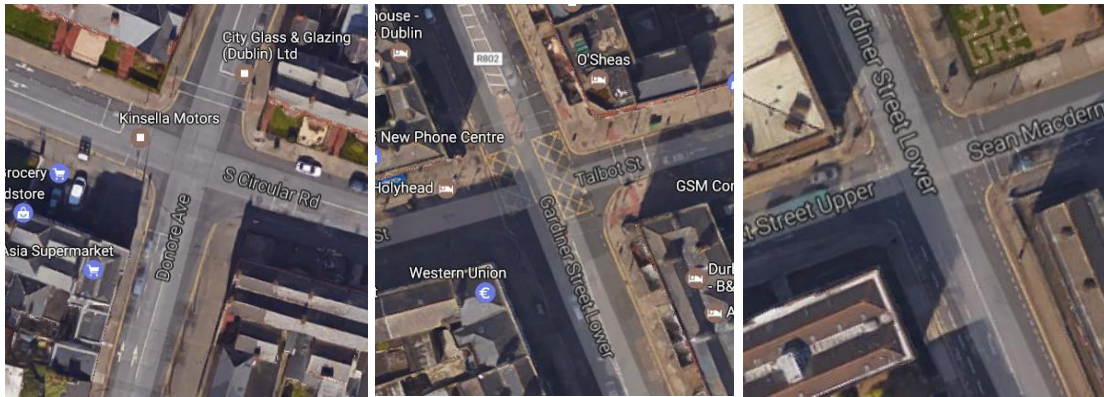


Figure 3.2 Detailed Google Maps satellite images from selected intersections from Dublin City (from left: Donore Avenue/South Circular Road, Talbot St/Lower Gardiner St and Sean Mac Dermott St/Lower Gardiner St)⁴

Additionally, weather data is provided by the DCC on rainfall measures for the given six months in 2016. The rainfall is measured by the DCC using a gauge with a tipping mechanism. The sensor is a device of two scoops divided by a layer that holds a magnet at the top. It has the possibility to empty its collected rain when one of the scoops reaches its limit. When rain flows into the scoop after passing a filter, it is caught there. When the volume of rain reaches the equivalent of 0.2 mm, the scoop is full and tips over. In this case, the magnet installed on the divider passes the ‘reed switch’. This switch being activated then sends an electrical signal to the system. As the depth of rain is measured with this rainfall measurement system, 1 mm of registered rain equals to 1 litre per square metre (O’Connor, 2016a). Therefore, this fact is used for the conducted analysis and work with this rainfall data.

Based on the rainfall data, the traffic data for the intersections can be analysed on potential changes in vehicle counts on days with heavy rain compared to days with no rain.

⁴ Donore Avenue: <https://www.google.ie/maps/@53.3314394,-6.2837129,18z>

Talbot Street: <https://www.google.ie/maps/@53.3506993,-6.2543033,19z>

Sean Mac Dermott Street: <https://www.google.ie/maps/@53.3530544,-6.2559958,19z> (Retrieved 09.12.2016)

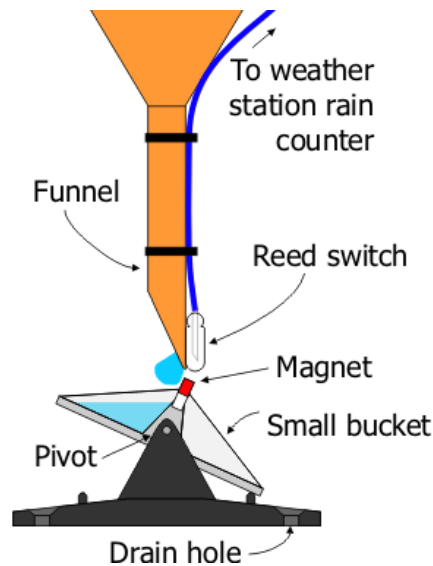


Figure 3.3 DCC rainfall measurement mechanism⁵

3.2.2 Data Preparation and Storage

All data is transformed into a format that can be used for further analysis and the simulation input. The software used for the data transformation is called Kettle. It is an open-source software by the Pentaho Community and can be used for data integration and transformation. The used dataset of traffic count data from inductive loops of intersections has the following parameters: time, intersection, approach and volume. The idea in this step is not only to remove the inconsistent data but also to divide up the fields of the dataset that hold too much data. This is true for the field time that holds a full timestamp with date and time. It is useful to have separate fields for the date and time portion to allow usage of both fields individually. The approach field also holds two sets of information: the approach and the detector number. These two parts are also divided during the preparation to differentiate between the two values. Over the course of the data usage as input data for the simulation and analysis only the information on the detector number is used from this point forward.

The rainfall data is also prepared in the way that it can be used for analysis and the simulation. Similar to the traffic count data, the time field holds the date and time information that should be separated to allow the summarisation of rainfall for each day. This is useful to present an overview of the rainfall extent.

⁵ The used picture is from the website <http://www.malvernwx.co.uk/about.htm> which is description of a British Weather Station but it uses the same rainfall measurement gauge as the Dublin City Council.

The transformed data is stored in a Microsoft Access Database which is part of Microsoft Office and integrated with Microsoft Excel that can be used to create tables and diagrams to provide a detailed analysis on the existing data.

3.2.3 Initial Data Analysis

Using the vehicle count data stored in the Microsoft Access Database, the traffic conditions existing at each individual intersection provide information on the volume levels of vehicles at intersections in Dublin. This data helps defining the experiments to be conducted for the project in greater detail.

The first point of the analysis is the comparison between the vehicle throughputs of the three given intersections. The basis for this is to summarise the vehicle counts for each intersection for the months January to June 2016. As shown in Figure 3.4 the selected intersections have different levels for registered throughput. The Donore Avenue intersection has the lowest throughput over all six given months ranging around 50000 vehicles per month. At the medium level with around 60000 vehicles per month is the intersection Talbot Street / Lower Gardiner Street. The highest monthly throughput with more than 80000 vehicles belongs to the intersection Sean Mac Dermott Street / Lower Gardiner Street. The months showing the highest vehicle counts passing any of the three intersections are March, April and May. The three different levels of throughput can be explained with the positions and the nature of the intersections.

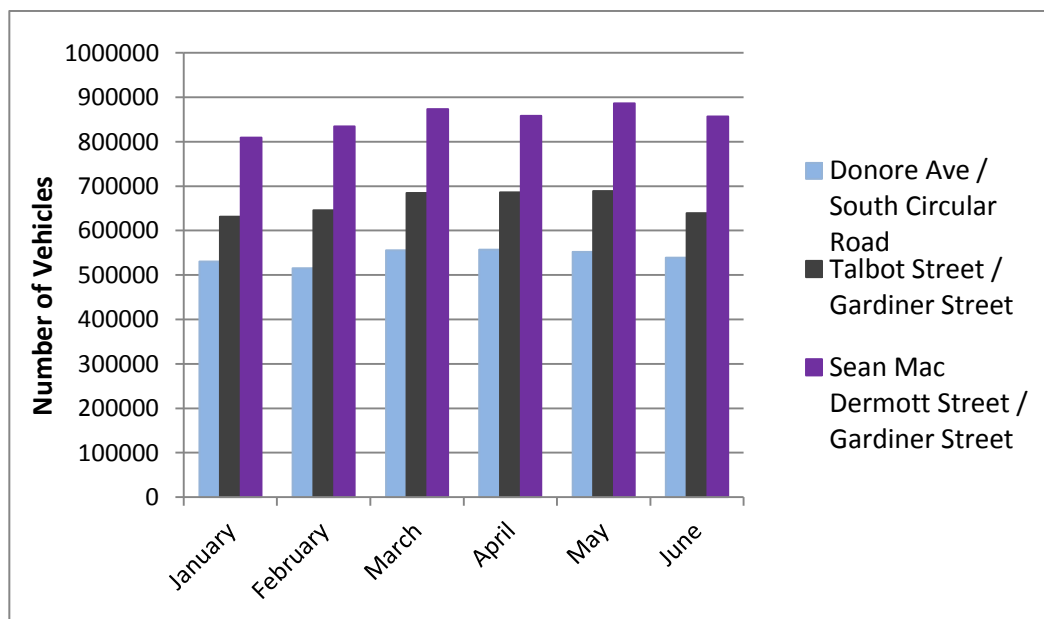


Figure 3.4 Monthly throughput for intersections

While Donore Avenue is an intersection on one of the important roads around Dublin, the other two intersections set on Lower Gardiner Street are positioned in immediate distance to the city centre. This causes the rise in traffic volume for these two intersections. The difference between the two central intersections is that at the Talbot Street junction there are only three input roads. This means that one road of the four-way intersections has no vehicles approaching the traffic lights because it is a one-way road leading away from the traffic lights.

The monthly vehicle throughput for the selected intersections provides a first insight into the volumes each traffic light control faces. This data is influenced by the number of working days or more specifically week days, weekend days and state holidays it contains. This information can also determine the traffic volume approaching any given intersection at a given time of a day. The day category holiday is defined by the used list of Irish state holidays for the six-month period (see Table 3.1).

Table 3.1 Relevant state holidays of Republic of Ireland for 2016 for the input data from DCC⁶

Date	State Holiday
01.01.2016	New Year's Day
17.03.2016	St Patrick's Day
28.03.2016	Easter Monday
02.05.2016	May Day
06.06.2016	June Bank Holiday

Weekdays are defined as any days between Monday and Friday not including state holidays. A weekend day is defined as either a Saturday or Sunday that is not a state holiday. The result as displayed in Figure 3.5 shows that there are in fact differences between the traffic volumes of a weekday, weekend or holiday. On weekdays the vehicle volume is lower in the early morning between 12am and 5am than on holidays and weekends. The latter two can be differentiated by higher volumes between 4am and 6am. 6am poses the point in time when the volume starts increasing exponentially for an hour that becomes the start of the morning peak time. The morning peak time with an average of 400 vehicles per 15 minutes lasts until 10am decreasing slightly

⁶ Retrieved from Public Holidays Global (<http://publicholidays.ie/>) on 30.12.2016

during this time before declining to approximately 350 vehicles at 10:30am. This level is kept for 2 hours before gradually rising to another peak time from 16:45pm to 18:45pm. The volume then drops to less than 250 vehicles per 15-minute timespan at 22:00pm. The traffic volumes for holidays and weekends do not show a specific peak time. They increase slower to their highest volume of around 300 vehicles in the afternoon with a moderate descent in vehicle throughput after 8pm.

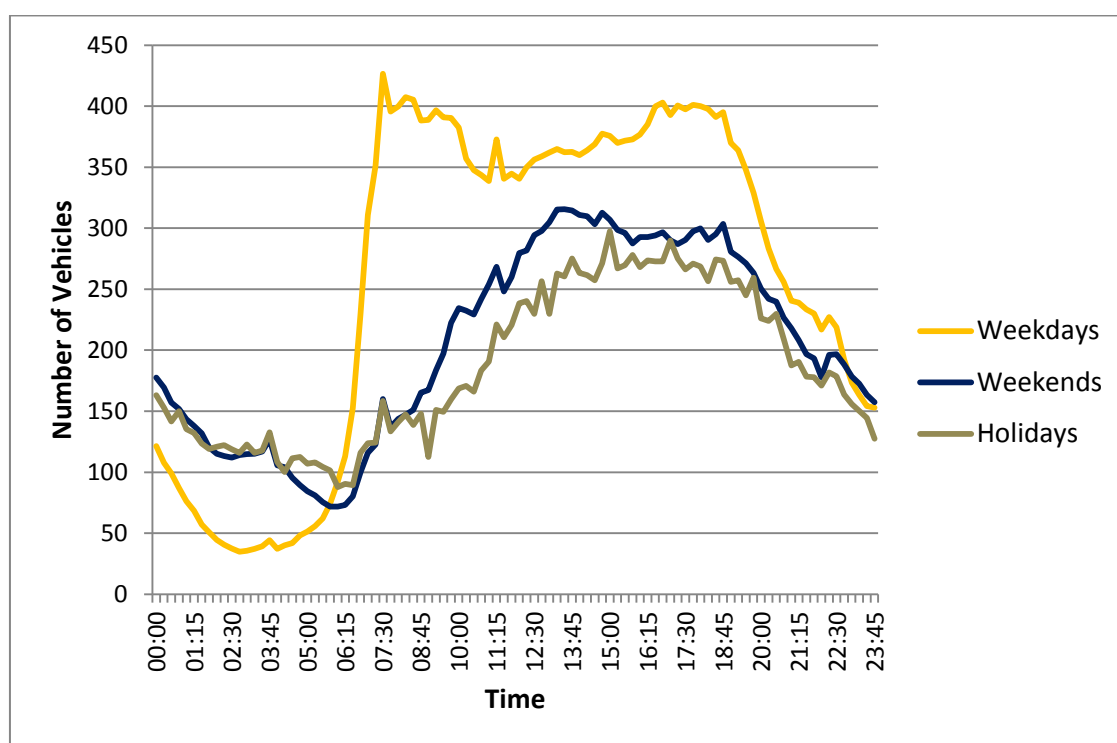


Figure 3.5 Average throughput per intersection for specific days

The daily sums of rainfall from the rainfall input data can be used to analyse the distribution of rain volume over the selected time. While the data only consists of the dates with collected rainfall signals, the remaining dates can be added to resulting daily totals. This daily rainfall provides the foundation to examine the rainfall data over the six months (see Figure 3.6). There are a large number of days with rainfall. A lot of these days only show a small amount of rainfall with less than 5 l/m² of rain a day. Considering this information only few days hold a rainfall volume of more than 10 l/m² of rain. Thus, a ‘rainy’ day is defined in this project as possessing a rainfall volume that is higher than 5 l/m². Every other day is counted as a ‘dry’ day.

The information from both examinations are combined to determine whether rainfall in Dublin influences the traffic volume approaching the intersections. Figure 3.7 shows the average throughput for an intersection in Dublin on a ‘dry’ weekday compared to a

‘rainy’ weekday. The development of both traffic volumes is very similar with a few differences containing some higher values during peak times on ‘dry’ days. On a ‘rainy’ day there is a rise in the throughput volume between 1pm and 3pm.

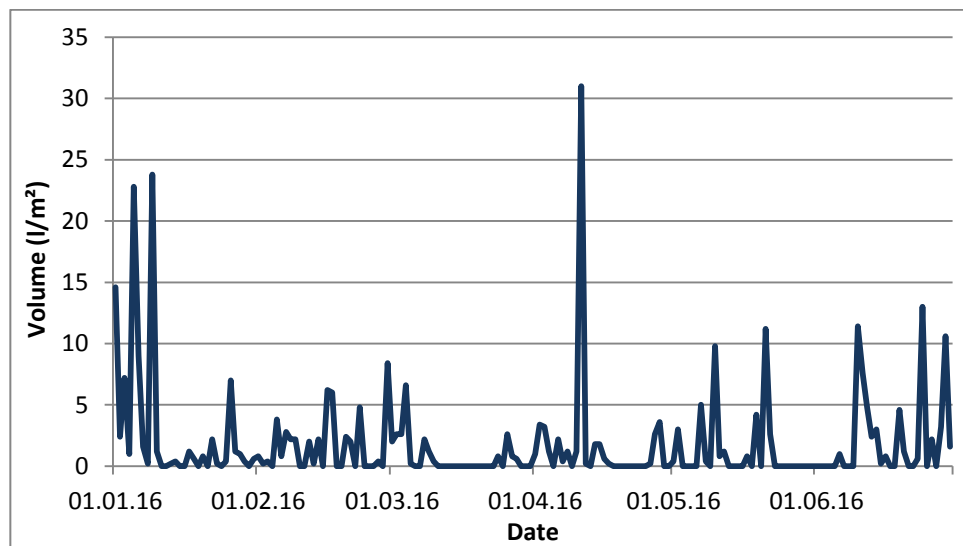


Figure 3.6 Daily rainfall for January - June 2016

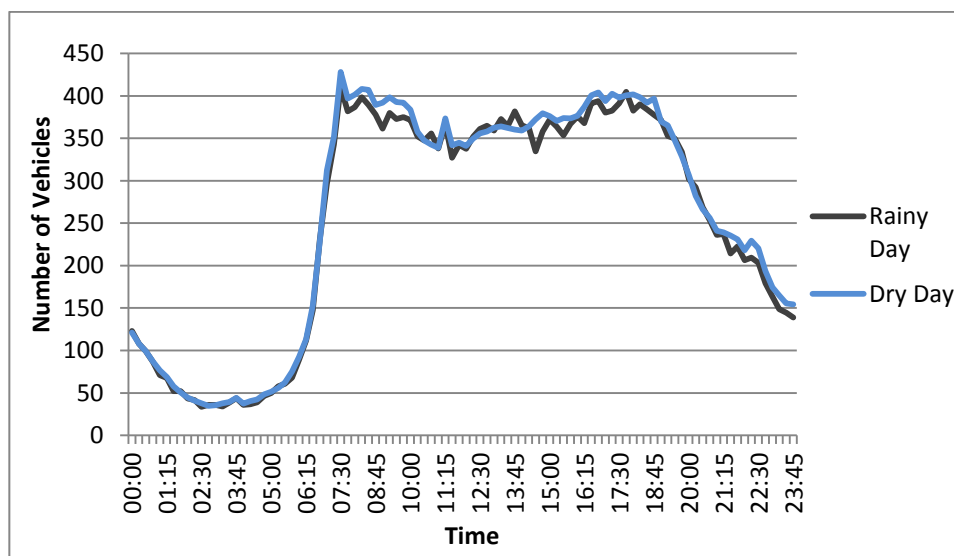


Figure 3.7 Average intersection throughput for weekdays with rainfall information

The traffic volume of a rainy weekend day is very similar to the throughput on a dry weekend day (see Figure 3.8). The recorded number of vehicles passing an intersection on a morning on a rainy weekend day is slightly lower than on a dry day before rising to higher numbers than the vehicle counts on a dry day during day time.

Figure 3.9 shows that the average throughput of holidays differs for rainy and dry days with lower vehicle counts for a dry day in the early morning hours until 6am. After 6am the traffic volume approaching an intersection on a dry day is significantly higher

than on a rainy day with an average of 50 vehicles difference. There is only one time during day time where the traffic volume of a dry and a rainy day are on the same level - at 2:30pm.

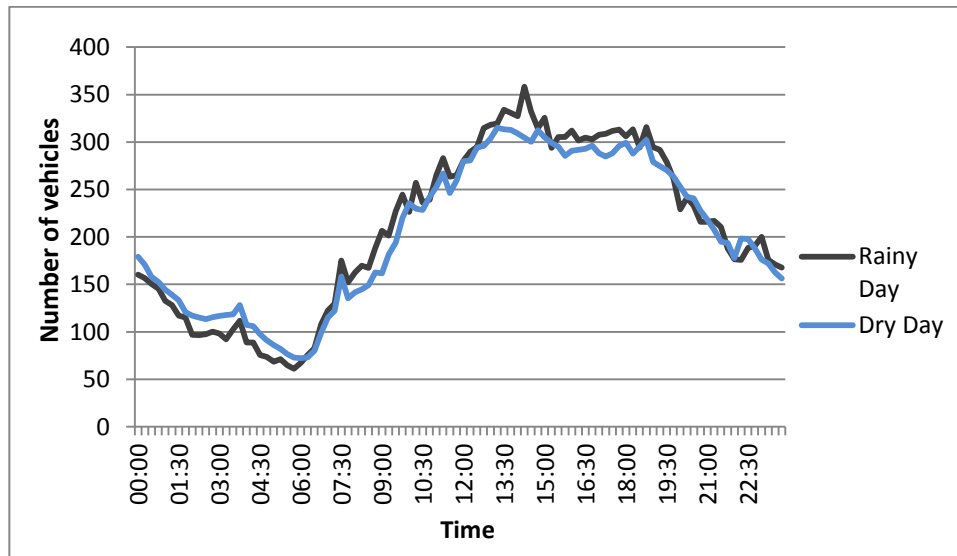


Figure 3.8 Average intersection throughput for weekends

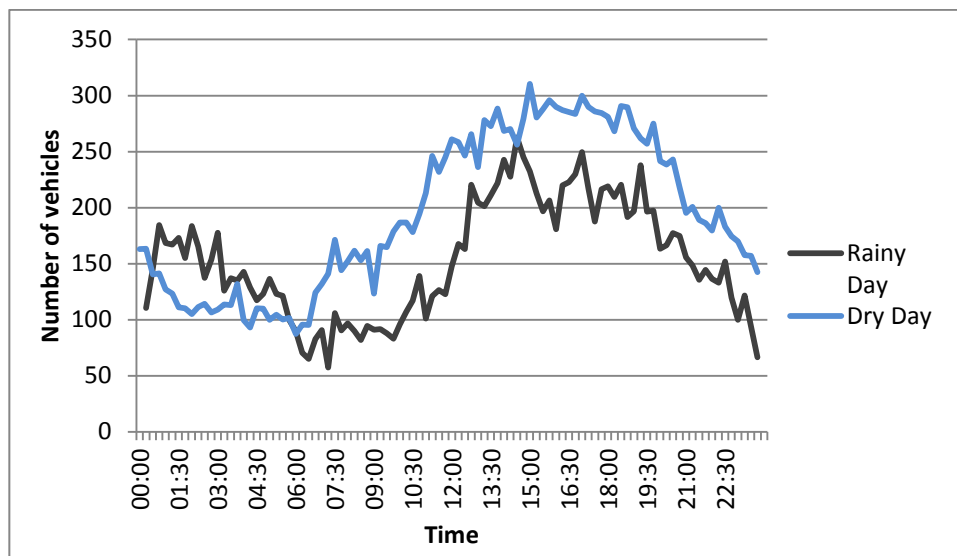


Figure 3.9 Average intersection throughput for holidays

As a result of this analysis of data from the DCC, the three selected intersections show different levels of traffic volume providing a suitable basis for the experiments and simulations to be conducted on the traffic conditions in Dublin. The throughput of an intersection depends not only on the time of day but also the day categories weekdays, weekend days and holidays. While the rainfall data is an interesting aspect for the traffic conditions in a city, the analysis only shows minimal effects on the recorded traffic volume for weekdays and weekends. The influence of rainfall on intersection

throughput on holidays is more significant. The next section describes the design of the experimental environment in detail.

3.3 Experiments

3.3.1 Description

The simulation tool SUMO provides the environment for analysing the efficiency and productivity levels of traffic lights in an urban environment. Information on working with SUMO can be found in its own established wiki as it is an open-source software. This source is used for the setup of the experiments. A SUMO simulation is based on several input files that define the layout of the road network and the vehicles moving across the given roads. The important element is the description of the network or in this case the individual intersection. The network is described within an XML-based file. The network can be created by using the tool NETCONVERT that belongs to the SUMO environment. This software turns simple XML files containing information on the network elements like nodes and edges into a full network description that can be used by SUMO. A node can represent an intersection or the end of a road. Roads in SUMO consist of one or two edges providing the information of the direction that vehicles can move in. In this case it means that each road can have two edges. One is the edge on which vehicles are approaching the intersection. The other is the one which they move along, once they have crossed the intersection and move away from the intersection. The edges not only have the information of the direction but also hold the data of the length of the road and the number of existing lanes⁷.

Additionally to these two compulsory NETCONVERT input files, there are optional files that hold descriptions of the edge-type and the connections between lanes. The first can define the level of priority of the edge and the number of lanes the type of edge contains. This allows the user to define the type only once and then use it multiple times in the edge description file⁸. The latter option defines the allowed moves of vehicles at a junction in SUMO by connecting the lanes of two edges with

⁷ SUMO wiki: http://sumo.dlr.de/wiki/Networks/Building_Networks_from_own_XML-descriptions (Retrieved December 20, 2016)

⁸ SUMO wiki: http://sumo.dlr.de/wiki/Networks/Building_Networks_from_own_XML-descriptions#Type_Descriptions (Retrieved December 20, 2016)

each other. By defining these connections, arrows are displayed on the specific lane at a junction that resembles the real arrows from intersections in Dublin⁹.

The information from the SCATS System installed at the DCC and Google Maps build the foundation for the established networks for the three selected intersections Donore Avenue, Talbot Street and Sean Mac Dermott Street. The SCATS system provides information on the number of lanes for each of the approaching roads. Google Maps information helps with the determination of the length of the roads. Based on this data the edge and node files are created to establish the network. Information from the vehicle count data on the traffic volume for each road helps to determine the priority for each road and image data from Google Maps sets the maximum allowed speed for the adjoining roads. The SCATS system data also specifies the basis for the connection description file. Using NETCONVERT, the data from these files is then transformed into the corresponding network file (see Figure 3.10). Testing the network in SUMO, the lengths of the edges are reduced to 60 metres to allow a detailed view of the intersection while also preserving the correctness of the simulation.

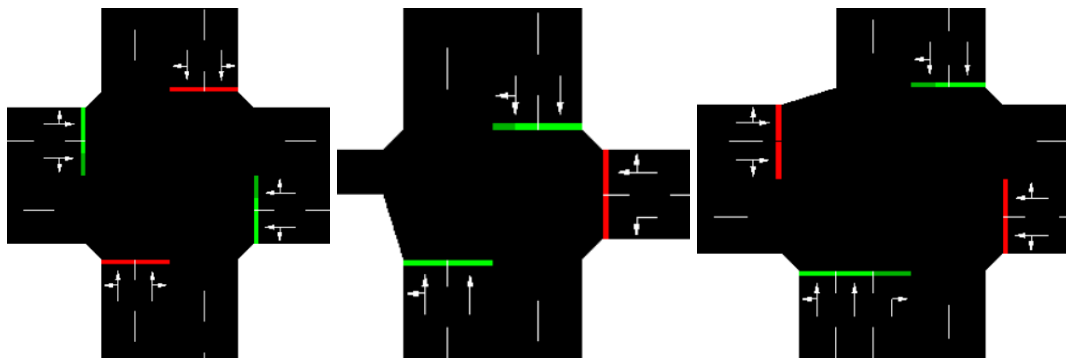


Figure 3.10 SUMO networks for the intersections in Dublin (from left: Donore Avenue/South Circular Road, Talbot St/Lower Gardiner St and Sean Mac Dermott St/Lower Gardiner St)

The final optional component of the network file is the traffic light program definition. This can be set in an individual file or is created automatically by NETCONVERT if not existent¹⁰. This component is an important aspect of the experimental part of this project. Thus, it will be described in more detail in the following section 3.3.2.

⁹ SUMO wiki: http://sumo.dlr.de/wiki/Networks/Building_Networks_from_own_XML-descriptions#Connection_Descriptions (Retrieved December 20, 2016)

¹⁰ SUMO wiki: http://sumo.dlr.de/wiki/Networks/Building_Networks_from_own_XML-descriptions#Traffic_Light_Program_Definition, http://sumo.dlr.de/wiki/Simulation/Traffic_Lights (Retrieved December 20, 2016)

The traffic count data can then be used to create the vehicle description files for SUMO to start the experiments. This file is also called 'route file' as it not only describes the vehicles moving through the network but also the route that the vehicle is following. The routes need to be defined first in the route file before associating a vehicle with route.

SUMO uses the unit 'second' for the time control of the simulation. A 'simulation second' can be set as equal to a second in the given input data time setting. When a simulation is run, a 'simulation second' does not equal to a real-time second to enhance the productivity of a simulation. This means that a simulation of a data time span of an hour is finished in a matter of a few seconds.

3.3.2 Simulated Traffic Light Control

With the input files for SUMO established and the network set up, the core of this project with the main intention of analysing the influence of the traffic light controls is used for the design of the experiments. The wiki from SUMO provides information on two included traffic light controls static and actuated that define the counter elements to the adaptive algorithm to be developed. SUMO uses the idea of traffic light programs to define the schedule of phases for a traffic light installed at an intersection in the network.

A traffic light program in SUMO is associated to only one traffic light, while a traffic light can have multiple programs. In the program the phases are described with their state and duration. The phases have to be declared in order as the program follows this defined sequence. The state defines the traffic light state for this phase. And it follows the order of North-East-South-West (NESW) for the individual segments. Each connection that is described in the connection file has its own state¹¹. In a technical manner, the traffic light program describes the traffic light cycle.

The traffic light experiments with the SUMO are divided into three parts:

1. Static Traffic Lights

NETCONVERT creates a static traffic light for a junction that is defined as a traffic-light controlled junction by default. The traffic lights of this intersection

¹¹ SUMO wiki: http://sumo.dlr.de/wiki/Simulation/Traffic_Lights (Retrieved December 20, 2016)

have a fixed schedule that cannot be changed. This means that the number of vehicles approaching the traffic lights have no influence on the traffic light rhythm. The created traffic light program is evaluated based on the phase definitions and time settings provided by the DCC.

Table 3.2 Static traffic light program

Phase No	Duration (secs)	State
0	31	All NS have green, while all EW have red
1	4	NS has amber, green continues NS right-turners; EW: red
2	6	NS right-turners have green; else: red
3	4	NS right-turners have amber; else: red
4	31	All EW have green, while all NS have red
5	4	EW has amber, green continues EW right-turners; NS: red
6	6	EW right-turners have green; else: red
7	4	EW right-turners have amber; else: red

As the generated program is very similar to a SCATS traffic light cycle, this program as shown in Table 3.2 is used to define the static light traffic control for the intersections. There are two important phases 0 and 4 that handle the highest throughput for the intersection. The phases 1, 3, 5 and 7 are included for safety reasons. Vehicles might still be in the intersection area when the green phase duration is over. To avoid accidents, these phases have a set time of 4 seconds. The SCATS system cycle and the static traffic light program both include 2 phases for right-turning cars at the intersection.

2. Actuated Traffic Lights

The second TLC provided and used by SUMO is the idea of actuated traffic lights. The actuated traffic light schedule is based on a traffic light control system predominantly used in Germany. It is a function integrated into the SUMO software and can be activated by the user. The traffic light schedule is based on a minimum and maximum duration for a green/red phase. The intersection is combined with existing inductive loops in the approaching links to the junction. Based on the distance between the detected vehicles, the green phase duration is

elongated or shortened within the set limits to accustom the existing traffic situation¹².

The actuated traffic light program used in the experiments is based on the static traffic light program with the difference of declaring minimum and maximum durations of 20 and 60 seconds, respectively. These limits are only defined for the two important phases 0 and 4. Only these two phases have the aspects of the actuated traffic lights, as amber phases should have a specific length for safety reasons. The green light duration for right-turning vehicles is set to its default length of 6 seconds.

Table 3.3 Actuated traffic light program

Phase No	Duration (secs)	State
0	20-60	All NS have green, while all EW have red
1	4	NS has amber, green continues NS right-turners; EW: red
2	6	NS right-turners have green; else: red
3	4	NS right-turners have amber; else: red
4	20-60	All EW have green, while all NS have red
5	4	EW has amber, green continues EW right-turners; NS: red
6	6	EW right-turners have green; else: red
7	4	EW right-turners have amber; else: red

3. Adaptive Traffic Light Control Algorithm

An adaptive TLC is proposed and developed within the course of this project. This algorithm presents the third approach to be tested within the conducted experiments. SUMO supports the usage of outside traffic light control mechanisms. The idea is to create a Python script with a dynamic algorithm that is not based on any specified times or durations given by the user. It is based on inductive loops that can be added to the approaching links of an intersection. Reading the number of passing vehicles the algorithm can change the phases in the

¹² SUMO wiki: http://sumo.dlr.de/wiki/Simulation/Traffic_Lights (Retrieved December 20, 2016)

cycle to fit the traffic conditions without the limitations of a set time schedule. The sensors provide data that can be read by the Python script using the Python version of the Traffic Control Interface (TraCI) interface of SUMO. This programming interface allows the script to set the times for the traffic lights and therefore control the cycle¹³.

This framework can be used for individual intersections to test the performance of each traffic light control strategy on the given data and traffic condition. The output of the simulations can then be evaluated and compared to provide a clearer view on the efficiency of each TLC approach.

3.3.3 Evaluation Measures of TLC Simulations

SUMO supports several different methods of output data to simulations of network traffic and TLC. Output data from SUMO is saved in XML files as defined by the user when starting a simulation. SUMO also supplies Python scripts that can transform an XML file into a CSV format and vice versa. The edge-based data can be generated during the simulation in specified periodic times. During each period the values are collected and aggregated. This output data includes information on the waiting time, the average speed and the average travel time per vehicle for the edge. The individual data is calculated by using the specific values of the existing lanes on the edge¹⁴.

Moreover, information on the queueing time and queue length can be generated by SUMO using the queue export option. In this setting, the lanes are checked every 'simulation second' to determine any queues and their attributes¹⁵.

While the edge waiting time and the queueing time are similar variables, the waiting time is linked to the edge whereas the queueing time is based on a queue in a lane. The waiting time defines the total time during the set period when vehicles are stopped. On

¹³ SUMO wiki: http://sumo.dlr.de/wiki/Simulation/Traffic_Lights,
http://sumo.dlr.de/wiki/Tutorials/TraCI4Traffic_Lights (Retrieved December 20, 2016)

¹⁴ SUMO wiki: http://sumo.dlr.de/wiki/Simulation/Output/Lane-_or_Edge-based_Traffic_Measures (Retrieved December 20, 2016)

¹⁵ SUMO wiki: <http://sumo.dlr.de/wiki/Simulation/Output/QueueOutput> (Retrieved December 20, 2016)

the other hand the queueing time is aggregated every simulation second and holds information on the development of the queueing time¹⁶.

The phase changing data from traffic lights at the intersection can also be exported from SUMO into an XML file. This means, that every time the phase changes within the defined traffic light program, this is registered and collected to create an output file. This information can be used to calculate the durations of each phase. This is helpful for the actuated and adaptive TLCs to determine the average, minimum and maximum durations for the green phases¹⁷.

Inductive loops are added to the SUMO road network for the adaptive TLC mechanism. Their definition also supports an option to generate output data on the loop sensors. The created data includes the number of passed vehicles. This measure can be used to evaluate the level of compatibility between the simulated data and the real world vehicle counts from the DCC¹⁸.

3.4 Adaptive Traffic Light Algorithm

3.4.1 Concept and Overview

The idea for the adaptive traffic light algorithm is to create a control mechanism that can change its phase durations based on the number of approaching cars, while also keeping the material and installation costs to a minimum. This results in the decision to use inductive loops as vehicle detectors. This decision provides the emerging possibility to use the existing inductive loops installed at the stop lines at numerous intersections in Dublin city.

The basic traffic light program is inspired by the generated program examples from SUMO for a static traffic light scheduling, while also including information collected during the literary research. As mentioned in chapter 2.4.4, the smaller the number of existing phases, the more efficient the scheduling strategy. Thus, the underlying traffic light program only consists of two green light phases: one for all movements from the

¹⁶ SUMO wiki: http://sumo.dlr.de/wiki/Simulation/Output/Lane-_or_Edge-based_Traffic_Measures, <http://sumo.dlr.de/wiki/Simulation/Output/QueueOutput> (Retrieved December 20, 2016)

¹⁷ SUMO wiki: http://sumo.dlr.de/wiki/Simulation/Output/Traffic_Lights#TLS_Switch_States (Retrieved December 20, 2016)

¹⁸ SUMO wiki: [http://sumo.dlr.de/wiki/Simulation/Output/Induction_Loops_Detectors_\(E1\)](http://sumo.dlr.de/wiki/Simulation/Output/Induction_Loops_Detectors_(E1)) (Retrieved December 20, 2016)

North-South (NS) direction and one for all movements from the East-West (EW) direction (see Figure 3.11).

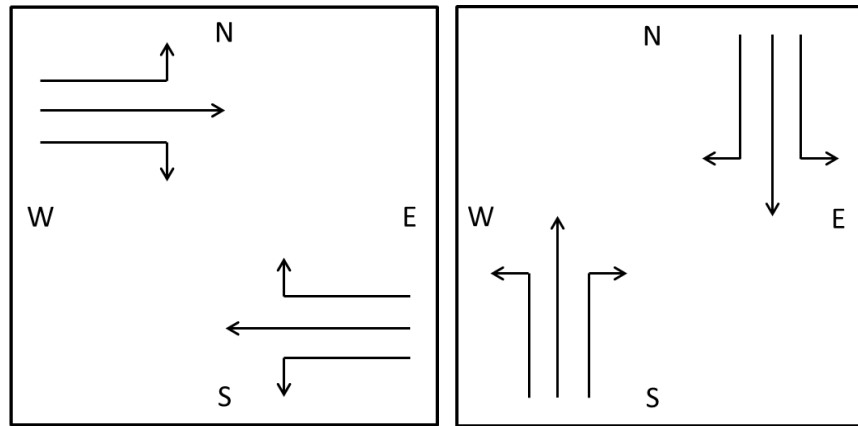


Figure 3.11 Two-phase system for the adaptive TLC algorithm – EW-direction and NS-direction

Table 3.4 Adaptive traffic light program

Phase No	Duration (secs)	State
0	20-80	All EW have green, while all NS have red
1	5	All EW have amber; else: red
2	20-80	All NS have green, while all EW have red
3	5	All NS have amber; else: red

As shown in Table 3.4, these phases have the numbers 2 and 0 for NS- and EW-direction, respectively. In between those phases is a set time for an amber phase with the duration of five seconds for safety measures. This two-phase approach not only simplifies the cycle time calculation and phase determination but also removes the decision process of the phase sequence. After phase 0 always comes phase 1 with the next green light phase 2. The minimum length of a green phase is twenty seconds, whereas the maximum length is eighty seconds. Based on the individual phase lengths within the set time span, the full cycle time can have a length between 50 and 160 seconds.

3.4.2 The Definition of the Adaptive TLC Algorithm

The adaptive traffic light algorithm is implemented using Python 3.5.2 and the IDE Eclipse Neon plus the additional Python library PyDev for Python support during development and debugging.

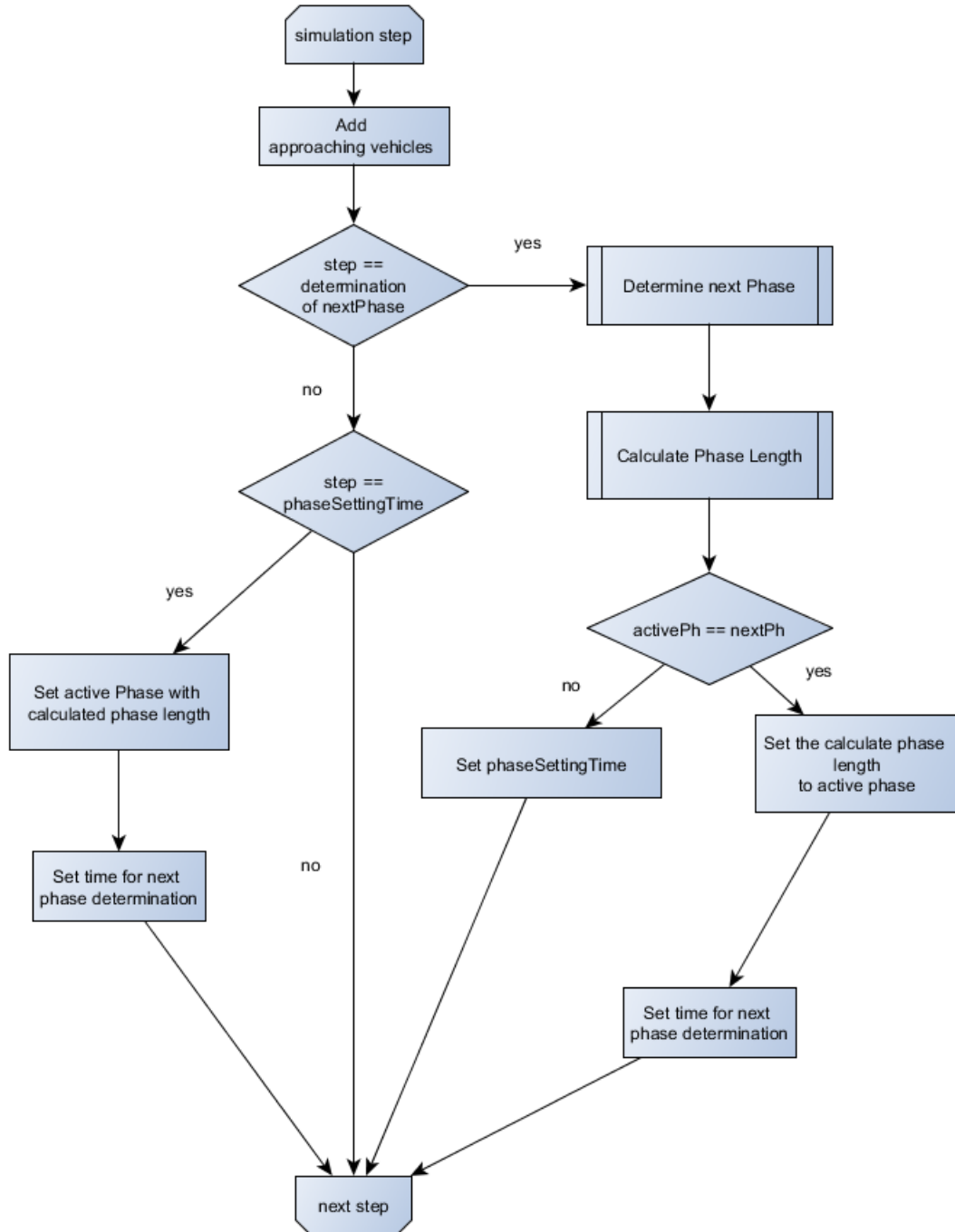


Figure 3.12 Main path of the adaptive TLC algorithm

Upon the start of the TLC program in Python, the available inductive loops from the description file (see chapter 3.3.1) installed in the edges are read. This determines the list of inductive loops assigned to the two green phases NS and EW. With the inductive loops associated, the SUMO simulation can be started and the TraCI connection opened. In this case, SUMO acts as a server with a port for the

communication with the TLC program acting as a client¹⁹. This provides the opportunity for the Python script to interact with the started simulation and control the traffic lights.

There are four variables that are important during the simulation run and kept at all times. This is the information on (1) the active phase, (2) the last green light duration, (3) the time step for the determination of the next phase and (4) the time when the duration of the phase has to be set when the green phase has to be changed. As the algorithm does not calculate the next cycle but only the duration of the next phase, this duration needs to be kept in memory. This information is used when the traffic light program is at the beginning of the determined phase to be able to set the calculated duration.

Once the simulation is started, the four variables are initialised. The length of the initial phase 0 is 30 seconds, meaning that the initial time step for the next phase determination equals 29 'simulation seconds'. As shown in Figure 3.12, on every simulation step, the numbers of vehicles that pass the inductive loops are added to the total number of approaching vehicles for each phase.

- Rule 1: If the active phase is 0 AND the number of approaching vehicles from NS is higher than or equal to the number of approaching vehicles from EW, the next phase will be 2.
- Rule 2: If the active phase is 0 AND the number of approaching vehicles from NS is lower than the number of approaching vehicles from EW AND the duration of the active phase higher than 60 seconds, the next phase will be 2.
- Rule 3: If the Rule 1 AND the Rule 2 are not true, then the next phase will be the active phase (0).
- Rule 4: If the active phase is 2 AND the number of approaching vehicles from EW is higher than or equal to the number of approaching vehicles from NS, the next phase will be 0.
- Rule 5: If the active phase is 2 AND the number of approaching vehicles from EW lower than the number of approaching vehicles from NS AND the duration of phase higher than 60 seconds, the next phase will be 0.
- Rule 6: If the Rule 4 and the Rule 5 are not true, then the next phase will be the active phase (2).

Figure 3.13 Rules for the next phase determination

¹⁹ SUMO wiki: <http://sumo.dlr.de/w/index.php?title=TraCI&%3Bolidid=7454>

There is a check at each simulation second whether the step number equals the number of simulation seconds at which the next phase has to be determined. If this is true, then the next phase is determined. This process is based on a few rules and three variables. The information on the active phase and the total numbers of approaching vehicles for the two green phases 0 and 2 are needed to conclude on the next green phase (see Figure 3.13).

Based on this decision, the length of the next phase can be calculated. It is used to select the option of extending the active phase or switching to the next amber phase to change the green phases. The length of the phase is adjusted by the information on the active phase, the determined next phase and the numbers for the approaching vehicles for the next phase directions (see Figure 3.14).

Initial: The phase duration is 20 seconds.
Rule 1: If the active phase is not equal to the next phase, the duration will 20 seconds.
Rule 2: If the Rule 1 is not true, the duration will be divided by the number of approaching vehicles for this phase direction. This is the new duration.
Rule 3: If the calculated duration higher than 60 seconds, the duration will be set equal to 60 seconds.

Figure 3.14 Rules for the calculation of the phase length

If the next phase and the active phase are equal, the active phase is prolonged by setting the length of the phase to the calculated length. The variable for the time step of the next green phase determination is set to the existing time step number plus the length of the calculated duration.

If the active phase differs from the next phase, the phase of the traffic light is switched to the active phase + 1 – that is the amber phase following the active green phase. The variable for setting the duration of the next green phase is set to the length of the amber phase plus 1 second. This is needed to ensure that the calculated green phase is active.

Regardless of the equality of the active phase compared to the next phase, the number of approaching vehicles for the direction of the next phase is reset to zero after the phase change. This reset allows a reasonable decision at the next phase determination process. It reduces the number of extensions for green light phases when they are not needed.

For every time step within the simulation when no phase is to be determined, the time step number is also compared to the variable for setting the green phase length. This

happens only in case of a green phase switch. If the variables are equal, the length of the active phase – which is the green light phase to be set – will be set to the calculated phase duration. This duration is by default 20 seconds.

At the end of the simulation, the TraCI connection is closed. The simulation of the adaptive TLC is ended by waiting for the termination of the SUMO process.

3.4.3 Analysis of the Characteristics

During the development process and theoretical simulations, it is useful to compare not only the results for different locations of the inductive loops (IL), but also adding multiple inductive loops per lane and an approach for advanced sensing on the roads. The latter is represented by using information that can be retrieved from the edges connecting to the intersection. This includes the number of vehicles on the edge at a given time.

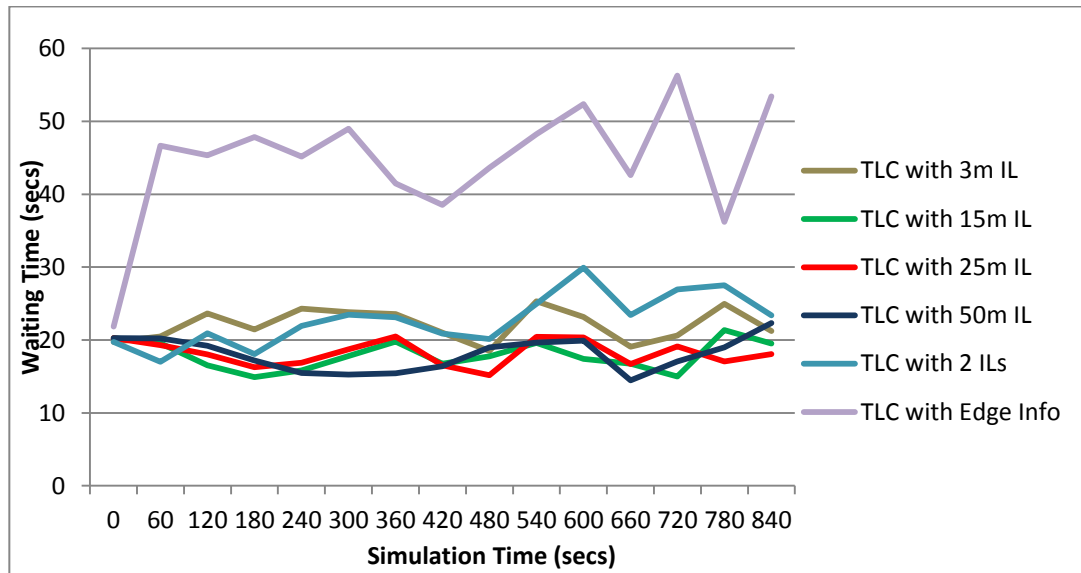


Figure 3.15 Waiting times for edges (period: 60 seconds) for the algorithm forms

Information on existing vehicles on the edges and the vehicle density can provide a more detailed view on the approaching number of vehicles. A similar approach to this idea is the use of two inductive loops for each lane. One of these loops is installed at a defined distance to the stop line, whereas the other one is positioned directly at the stop line. Thus, the number of vehicles in the area between the inductive loops can be determined. These vehicles depend on the green phase duration the most. In this project these distances are set as follows: 50m for the distant loop and 3m for the close loop.

On the single inductive loop tests, the distance to the traffic lights are altered between 3m, 15m and 50m. The simulation is run for a low and high number of vehicles approaching each of the intersections. The development of the average waiting time across all conducted tests is used to compare the efficiency between the different adaptive TLC forms (see Figure 3.15). The three forms with the highest average waiting times are the algorithms that use two inductive loops, the information from the edges and the inductive loops positioned directly at the stop line. The form with advanced sensing information produces the highest waiting times with an average of more than 20 seconds above the other algorithms.

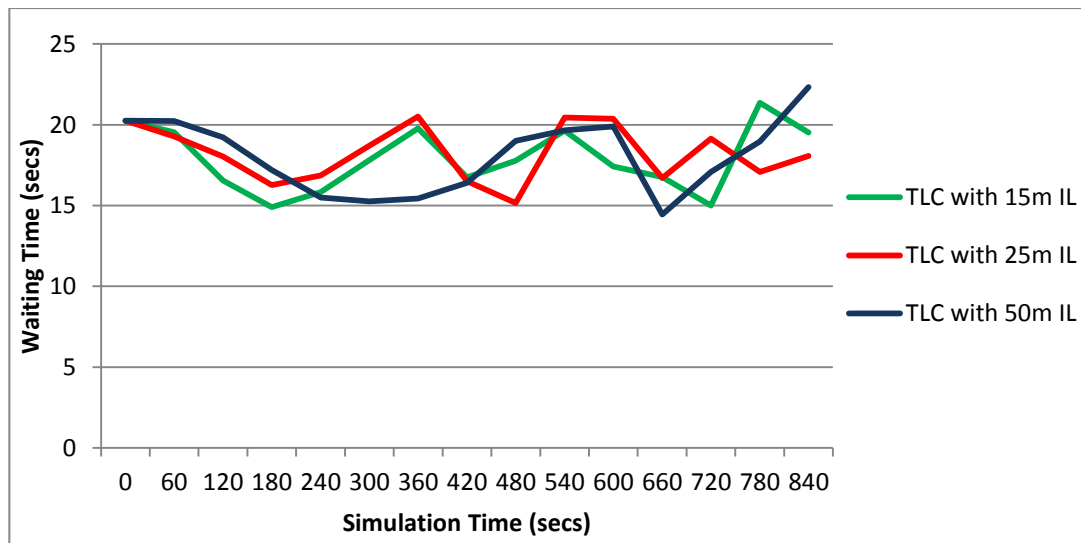


Figure 3.16 Detailed view of the waiting times for edges (period: 60 secs)

While the other two are closer to the algorithms using inductive loops at 15m or 50m distance, their average waiting times are still higher. With the two leading variations of the algorithms having inductive loops at 15 and 50 metres distance, an additional test is conducted using the distance of 25 metres. This is positioned in between the two most successful positions. Figure 3.16 shows a more detailed version of the comparison between the three remaining algorithms. The decision to add the variation with the inductive loop at 25m proves to be favorable as the development of the average waiting time produces a graph similar to the algorithm with a 15m IL. It provides lower maximum values compared to the other two leading algorithm forms.

Based on the results from this comparison, the conclusion is to apply the inductive loops installed at a distance of 25m to define the final algorithm. This version is used in the experiments and analysis with the static and actuated TLCs.

3.5 Simulation Automation Software

The vehicle counts detected by the inductive loops have to be translated into the vehicles moving along routes for the simulation to be able to run. There is a need to automate this process and the individual simulations with the three TLC approaches static, actuated and adaptive. A solution for this problem is a tool that can run the simulations for all three TLCs using the data provided. Based on specific settings, the automation strategy is changed to adapt to the user's context. The user should be able to select the types of TLC simulations to be run. This allows the production of only one or two approaches. It also provides the ability for a full comparison between the individual traffic light scheduling approaches. It provides the functionality to run the simulations multiple times as a way to enhance the resulting data in size.

The transformed data stored in the database is separated in date and time information, as detailed in chapter 3.2.2. This provides the possibility for the tool to allow the user to define the date and time span of the simulated data separately as needed. Each of the settings determines which data records are used for the calculation of the average vehicle counts per detector. With a minimum and maximum date the amount of data can be reduced to for example a month, a week or one single day. The selected minimum and maximum times determine the daily time that is used. This setting not only selects the amount of data retrieved from the database, but also dictates the length of each individual simulation. The vehicle count records in the database present 15-minute intervals (900 seconds) for each day. Based on these periods, the duration of the simulation is calculated by summing up the simulation seconds.

An important aspect is to choose the intersection to retrieve the detector data from the database and the corresponding network description for the simulation.

As referenced in the input data analysis, there is a distinctive difference between the daily development of intersection throughputs on holidays, weekdays and weekends. This day information should be available for selection to refine the simulation data. Finally, the rainfall data should be available in combination with the day selection to choose between a rainy and dry day.

These settings determine the design of the user interface (UI) for the automation tool to provide a simple configuration option for the user. The resulting UI is shown in Figure 3.17. It includes all the described settings to vary the simulation environment and

process based on the user's needs. An additional feature is the 'Start' button to launch the automated simulation process (see Figure 3.17).

Figure 3.17 UI for the Simulation Automation Tool

The information on the available intersections is stored in the database to not only allow the separation of the display value and the intersection number that is inherited from the DCC's SCATS system. The minimum and maximum dates in the date selection are also taken from the database to make this information as flexible as possible.

At the beginning of the automated simulation process the settings are read from the UI to provide the information needed to retrieve the data from the database. An SQL query using an ODBC connection to the Microsoft Access database is sent for each 15-minute period until the time is higher than the selected end time. This process is used to retrieve the detector data for interval. To create the vehicles that move along the roads in SUMO, information on the created route definitions is needed. This information is stored in a route description file in XML format. A table is created to associate the vehicles from a specific detector with a route definition to avoid the

complex parsing of XML files. Thus, only an additional SQL query has to be executed to retrieve this information.

Using the vehicle counts and the route information the vehicles can be created. SUMO provides the option to define so-called flows²⁰ that are streams of vehicles. A flow has the following attributes: a specified start time, end time and the number of vehicles emitted at the start of the associated route within that time period. This last attribute can be used for this case as the vehicle counts from the records stored in the database represent the same measure without any needed transformation.

With these vehicle flow objects constructed, the route file can be created with the route description file for the intersection. The flows are added after being converted to their corresponding XML-formatted strings. This route file is the important input file that is needed in combination with the network file for the simulation to be run.

An additional file is created that defines the output options of the simulation. Here the file contains the options for the output of edge-based data and the registered switches in the traffic light states.

For each automated simulation test, a new folder is created to save the created input and generated output files from SUMO.

A corresponding configuration file for SUMO is created for every selected TLC approach that is needed to run the simulation. This config file holds the information on the network file, the created route file, the start and end time of the simulation, plus the option for queue based output. With the config file generated, the SUMO process can be started with the input parameter for the prefix of the output filenames. This prefix consists of the start time of the simulation and the TLC type. The same config file is used multiple times for the simulation execution according to the defined number of test runs (see Figure 3.17).

When the simulations for all TLCs are finished, the output files can be transformed into the necessary format for analysis. In a first step, the XML files need to be converted into CSV files by a SUMO tool. It is a Python script called *xml2csv.py*. These CSV files can then be formatted and combined to provide one final output file

²⁰ SUMO wiki:

http://sumo.dlr.de/w/index.php?title=Definition_of_Vehicles%2C_Vehicle_Types%2C_and_Routes&%3Boldid=8423#Repeated_vehicles_.28Flows.29

for each individual output type. Each line of data from the transformed CSV output files is read to remove unnecessary data and add data on the test run before adding it to the final output file. This additional data contains the intersection number, the timestamp of the test run, the settings for the day type, weather type and finally the analysis type. The last field is used to separate the different experiments from each other.

The information on the traffic light state switches holds data on the times when the phases of the traffic lights are changed. Each line within the CSV file holds the time of the switch and the phase the traffic light switched to. As this information is not as useful as the duration for each phase, this output data requires some calculations. The duration for each state can easily be calculated by subtracting the time step value of the current line from the time value of the next line or in this case the next phase switch. The information on the phase from this next line is saved in a variable outside the loop reading the lines of the file to preserve this phase information for the next calculation.

There are four final output files. They hold data on edges, loop detector, queues and the traffic light states. As they are CSV files, they can easily be added to the Microsoft Access database into the four corresponding tables as external data files. The additional data added to each of the lines in the final output files is repeating itself in each line.

To simplify the following analysis, the CSV files are stored in the database without eliminating the data duplications in several fields. This proceeding can be seen as equivalent to the storage of data in a data warehouse. This provides the positive effect of enhancing the performance of SQL requests for the analysis.

4 EXPERIMENTS AND RESULTS

4.1 Overview

This chapter aims to describe the conducted experiments using the automated simulation tool SUMO and their results. An essential step for the experimental procedure is the evaluation of the input data and is therefore outlined in the first section. There are four experiments performed on the three TLC approaches to compare their performances and effectiveness on multiple levels. The experiments are ordered by the used time span selected for the simulations. The first experiment is based on a single 15-minute time span, followed by two experiments with time spans of an hour to the final experiment that uses the data of a full day as a time span for the simulation.

4.2 Evaluation of Input Data

The evaluation of the data provided by the DCC against the inductive loop data generated by SUMO is needed. It holds the information whether the simulations model the documented traffic conditions for Dublin successfully. Negative results of this test pose a need for adjustments of the vehicle counts retrieved from the database to create a more appropriate model. In this case, the number of vehicles associated with the flows in the generated route file cannot just use the plain vehicle counts from the inductive loop data.

The automated simulation tool is used to run the evaluation tests and produce the data needed. The selected test cases are holidays and weekends with no weather restriction and rainy weekdays. Each of the input data has the date span of the full six months and the time span of a full day. The generated output data for the inductive loops installed in the lanes holds the information of the number of passed vehicles. The interval for loop data is 900 simulation seconds which equals the 15-minute interval found in the DCC data. This period is used to allow a value-by-value comparison of the input and output data. As the tests are run on all three intersections, an average intersection throughput is calculated for each test case. The throughput is computed by creating the sum of the individual detector counts for every interval for each intersection. These intersection throughputs are then used to create the final mean throughput per interval.

Figure 4.1, Figure 4.2 and Figure 4.3 show the differences between the input and output data on rainy weekdays, holidays and weekends. The graphs for recorded vehicle counts from the DCC and the detected vehicles from the loop sensors in the SUMO simulations for holidays and weekends show visibly no divergence. On rainy weekdays there are some minimal discrepancies in the traffic volumes during the day time between 8am and 8pm.

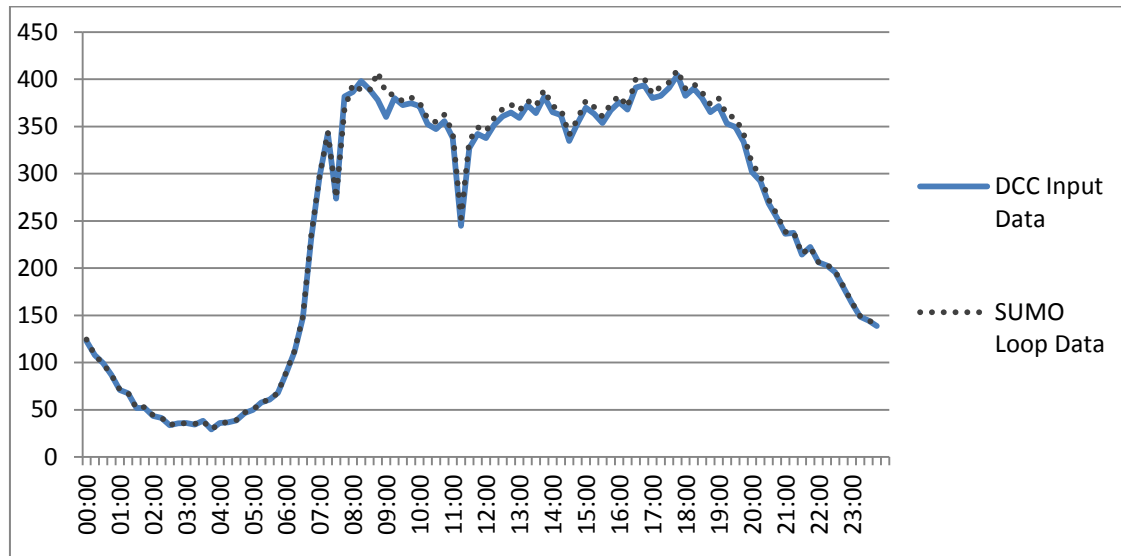


Figure 4.1 Comparison between input and output loop data converted to average intersection throughput on rainy weekdays

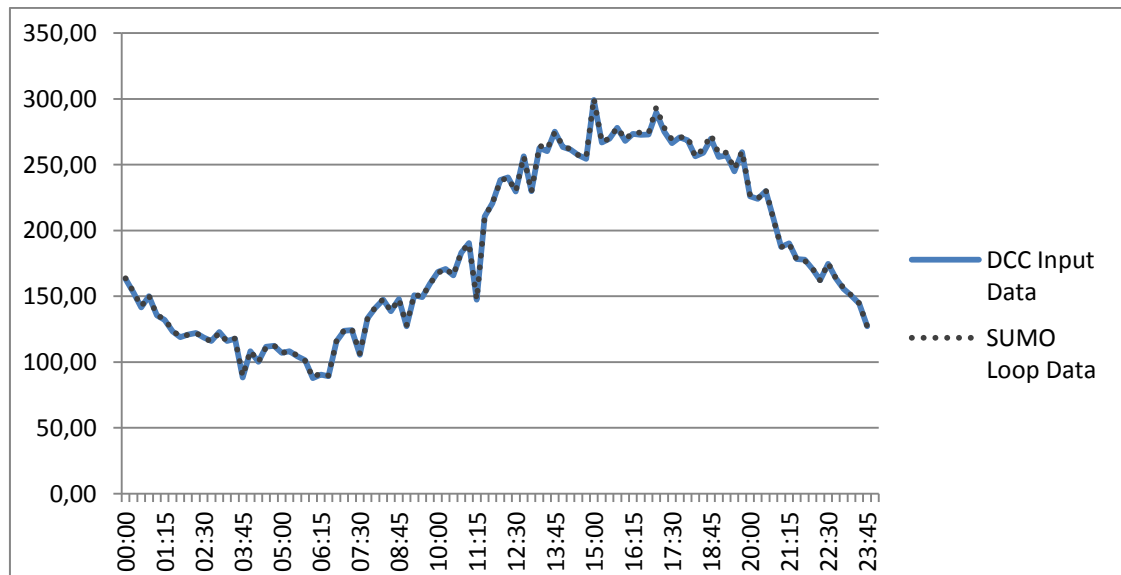


Figure 4.2 Comparison between input and output loop data converted to average intersection throughput on holidays

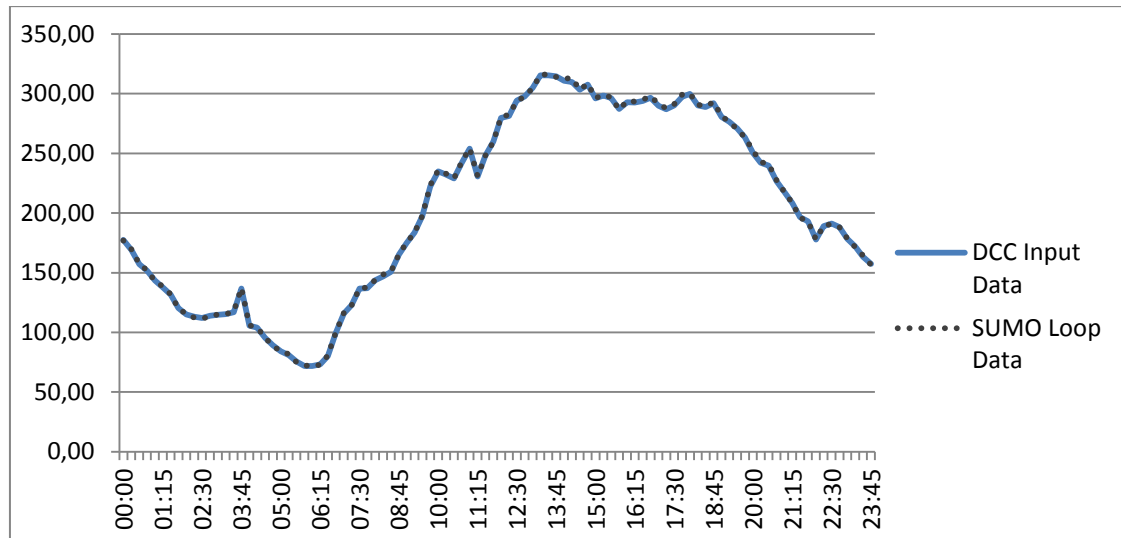


Figure 4.3 Comparison between input and output loop data converted to average intersection throughput on weekends

These small differences can be explained by the location of the inductive loops in the simulation used for the detection of vehicles. The inductive loops are positioned at a 25-metre distance to the stop line as they also serve the purpose of detecting the approaching traffic volume for the adaptive TLC. The vehicle counts recorded by the DCC are from inductive loops positioned directly at the stop line and therefore count the number of vehicles that actually pass the intersection in the 15-minute intervals.

Moreover, when retrieving the average vehicle counts for each detector from the database, the returned double values are rounded to the nearest integer value as the flow objects in the route file only take integer values as input data.

As mentioned above, while the causes for differences between input data and output data are discussed, the effects are either non-existent or minimal. This results in the conclusion, that the tests that are conducted within this project can use the plain vehicle count data from the database as input data for the simulations.

4.3 Experiment 1: Vehicle Volumes

4.3.1 Overview

The first experiment examines the effectiveness of the TLC approaches at increasing volume levels of approaching vehicles. The throughputs for the intersections are analysed for the levels of the traffic volumes. This shows that the throughput for the intersections Donore Avenue, Talbot Street and Sean Mac Dermott Street spans

between below 50 to a maximum of 480 detected vehicles per 15-minute interval. The volume levels tested in this experiment therefore start with 50 vehicles and increase by 50 vehicles each time. The idea is to find five time samples in the day categories weekends, holidays and weekdays, where the intersection throughput with the 15-minute interval is equal to or within a deviation of 5-10 vehicles of the defined vehicle levels. These are 50, 100, 150, 200, 250, 300, 350, 400 and above 450 approaching vehicles.

The frequency for the edge-based output is set to every 60 seconds to provide the necessary information for the analysis of the output data.

4.3.2 Results

The first comparison of the output data, as shown in Figure 4.4, does not include the TLC information but aims to analyse the development of average waiting times for the individual intersections. All waiting times for an intersection at a volume level are used to compute the numerical mean. The average delay increases with the number of vehicles approaching the traffic lights with a minimum delay of less than 10 seconds at 50 vehicles and a maximum of nearly 60 seconds at over 450 vehicles. There are slightly shorter waiting times for the intersection Talbot Street compared to the other two intersections at all vehicle volume levels.

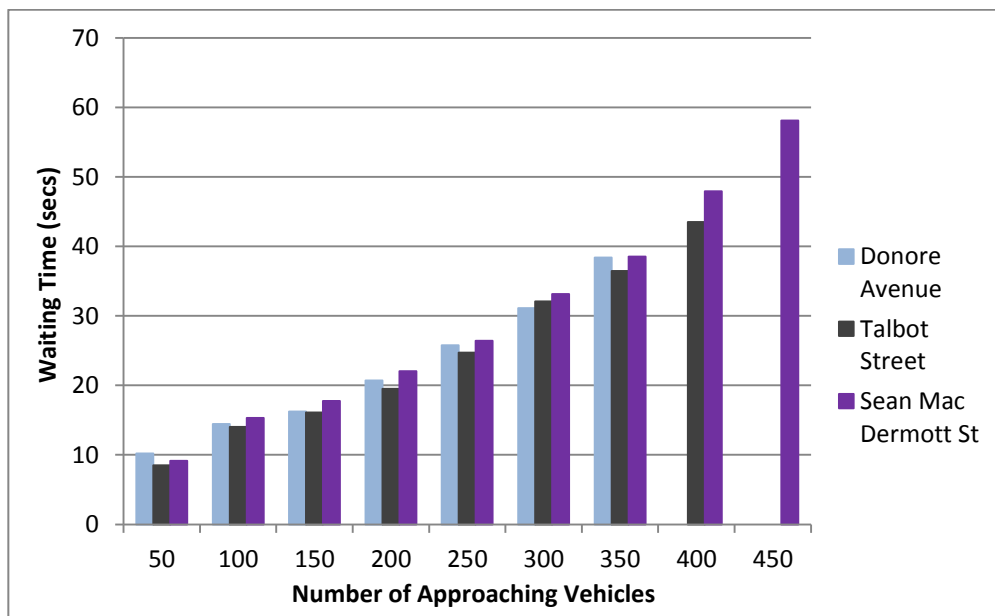


Figure 4.4 Development of average waiting time for each intersection based on the vehicle volume

Figure 4.4 also shows that no test cases from the intersection Donore Avenue were used in the two highest volume levels. This is based on the fact that the traffic volume at this intersection is not as high as the other two intersections. Also, no test cases can be found from the Talbot St intersection for the level of 450 approaching vehicles with a similar reason (see chapter 3.2.3).

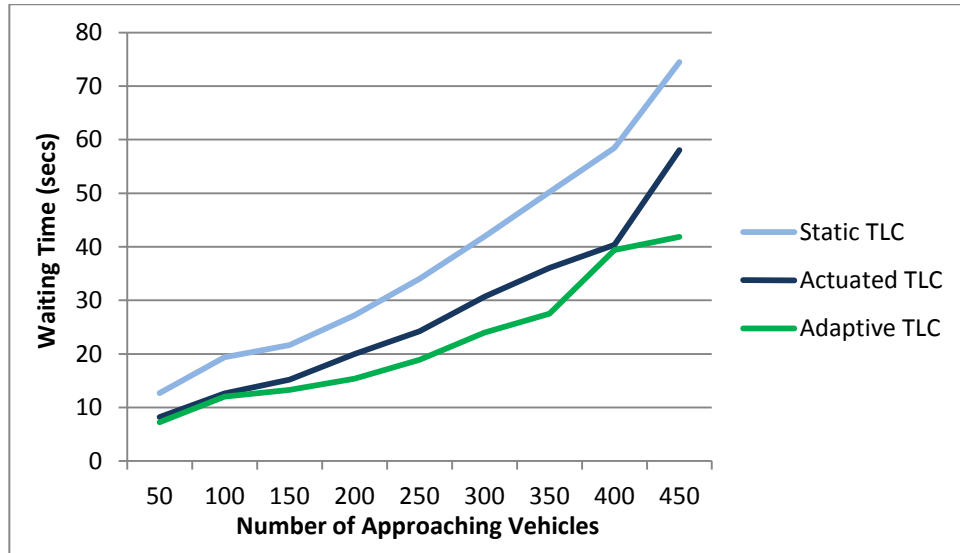


Figure 4.5 Average waiting times based on TLC for increasing vehicle volumes

The minimal existing discrepancy between the waiting times of the intersections allows the combined analysis of the waiting times regarding the TLC approaches. The Figure 4.5 describes the progression of the average waiting times for the vehicle volume levels. The static TLC produces the highest delays compared to the other two starting with 5 seconds difference that grows to over 10 seconds longer waiting time above an intersection throughput of 300 vehicles. While the delays generated by the actuated TLC lie between the adaptive and static traffic lights in range, they are closer to the stop times formed from the adaptive traffic light scheduling.

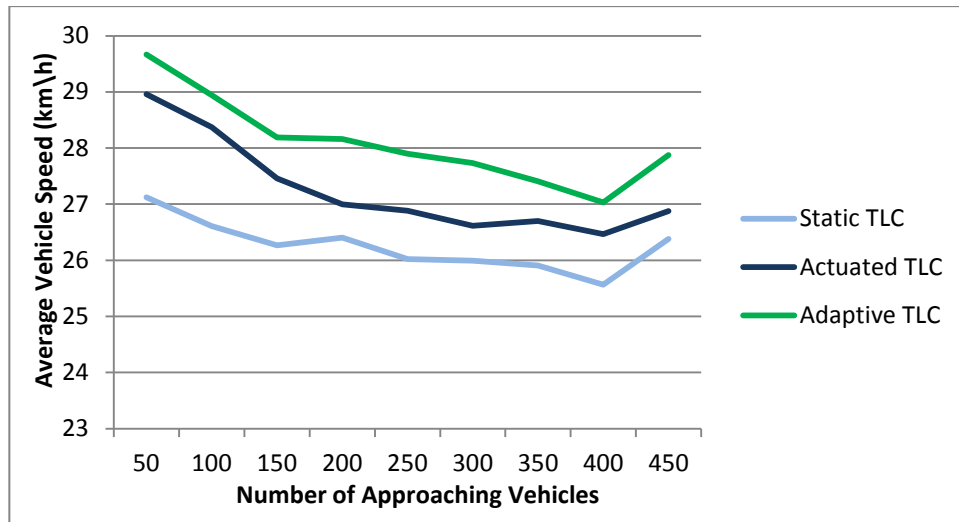


Figure 4.6 Average speed per vehicle for increasing vehicle volumes

Reducing the waiting time at a red phase increases the average speed of vehicles along the roads in the network (see Figure 4.6). As the static TLC presents the highest delays, its average vehicle speeds are the lowest numbers with a range between 25.6 km/h and 27 km/h. The graph for the actuated TLC starts out at 29 km/h for 50 vehicles before dropping to the lowest point of 26.5 km/h, proving to produce a higher speed than the static TLC. The highest average speeds overall are reported for the adaptive TLC.

With an increasing vehicle volume, the average speed drops for all TLC approaches before rising at the highest volume. This can be a result from the discrepancies between the intersections. The Talbot Street has only six approaching lanes from three directions that comprehend the same vehicle volume levels as the other two intersections having four directions and eight or nine approaching lanes.

Speed and waiting times are only two variables that are provided by the output file on the approaching roads. A third measure is the travel time which is the needed time a vehicle spends on the roads approaching the intersection. The development of the average travel time per vehicle for the increasing throughput volume levels is displayed in Figure 4.7. The time needed to pass the stop line at the intersection drops slightly when a higher volume of vehicles approaches the intersections. The adaptive TLC produces the lowest travel times with durations of less than 14 seconds, followed by the actuated TLC with a range between 14 and 16 seconds. The highest travel times are generated by the static traffic lights.

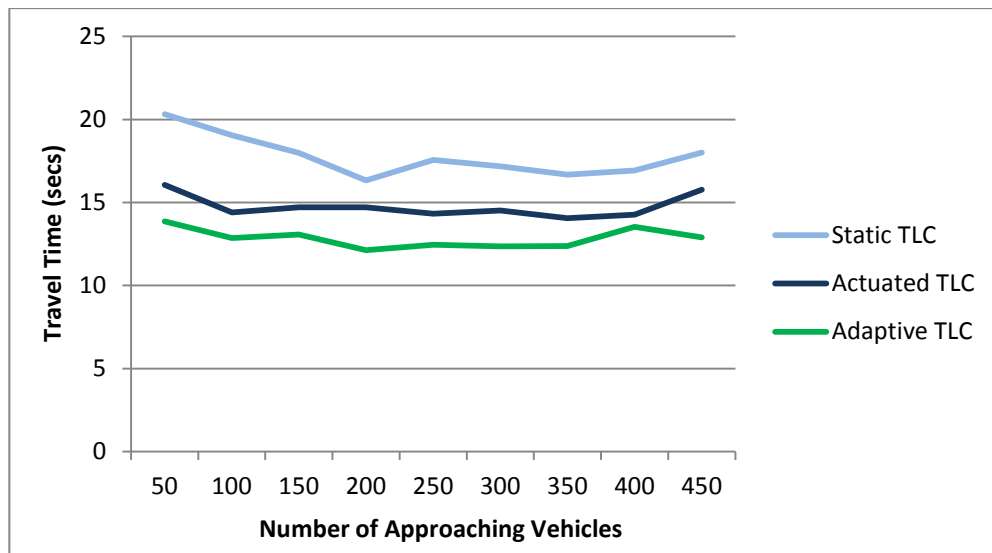


Figure 4.7 Average travel time for all vehicle volume levels

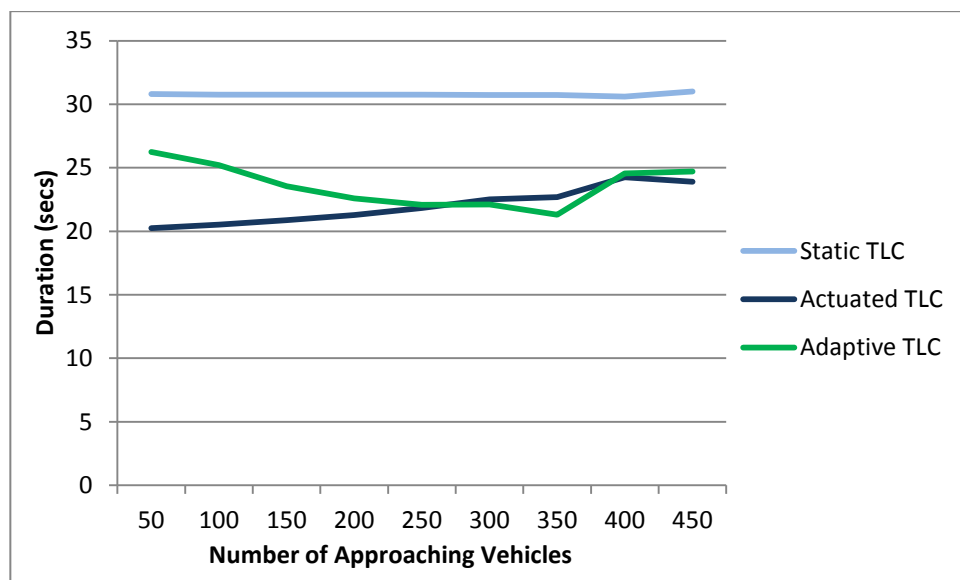


Figure 4.8 Average length of green light phases for the increasing vehicle volumes

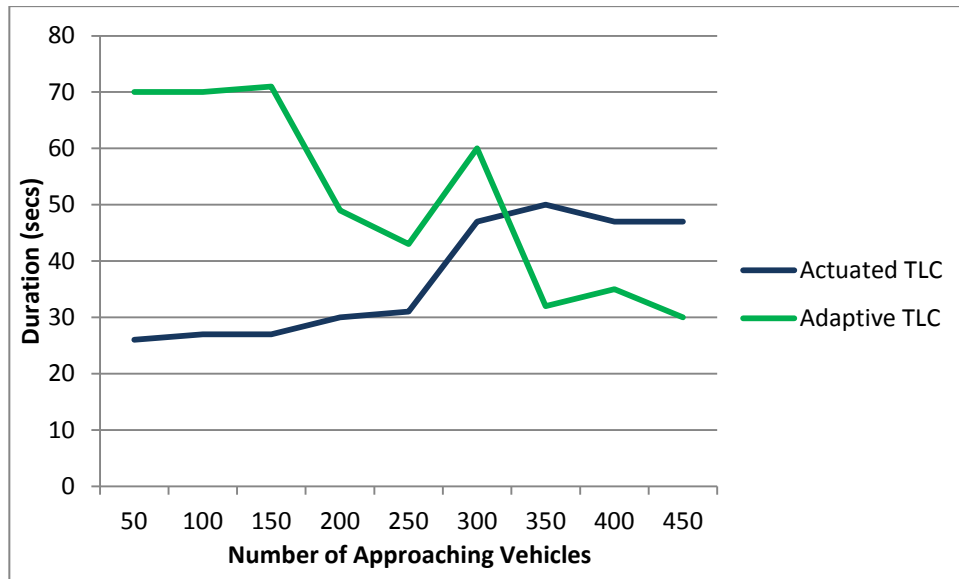


Figure 4.9 Maximum length for the green light phases for actuated and adaptive TLCs

As durations of the green light phases vary for the actuated and adaptive TLC, it is useful to analyse these durations in the mathematical features of mean and maximum values. Figure 4.8 shows the average lengths of the main green phases in all three tested TLCs.

The static TLC has a consistent value of just below 31 seconds as the green phase duration for one intersection is defined with 31 seconds. While the medium length of the main green phases for the actuated TLC increases gradually from 20 seconds to just below 25 seconds, the phase lengths computed by the adaptive TLC algorithm starts out with a longer phase duration, but falls with the increase of approaching vehicles. The maximum values for the green phase durations are corresponding to the average phase lengths (see Figure 4.9). An incline can be seen for the phase durations with the actuated TLC and a general decline with the adaptive TLC. There is a rise of 15 seconds to 60 seconds at the volume level of 300 vehicles.

4.4 Experiment 2: Consistent Traffic Conditions over the time span of one hour

4.4.1 Overview

After the short time blocks and their throughput numbers being analysed in the section above, this experiment aims to show the influence of the TLC approaches on consistent traffic conditions. They are defined within this project as consistent approaching number of vehicles over the time span of one hour. This means, that the

values only vary within a range of 5 to 10 vehicles approaching the intersection. For this experiment seven test cases are found for each intersection. These samples do not only have consistent traffic conditions but also represent at all vehicle volume levels in the best case. This is to provide the sufficient evaluation of experimental results for consistent traffic conditions for an intersection with one of the TLC approaches.

The edge based output is set to a 60-second interval to provide detailed information on the waiting time from the simulation tests on the actual delays experienced by each vehicle.

4.4.2 Results

The test cases are divided into the two groups with low and high throughputs with in the consistent traffic conditions. This is based on the results acquired during the first experiment, see chapter 4.3.

The results show variances are caused by the number of approaching vehicles. This information is used for the group definitions. The low volume group holds test cases where the throughput for each 15-minute block only totals to a maximum of 110 approaching vehicles. On the other hand, the high volume group contains consistent traffic condition samples where the minimum throughput is above 270 vehicles. The minimum is originally set to 250 approaching vehicles per 15-minute time unit, but the existing samples found with the condition set for the consistent traffic conditions, as mentioned above, exhibit a minimum of 272 vehicles.

As expected, the waiting times for the low volume group are significantly lower at around 10 seconds for all TLCs than the high volume samples (see Figure 4.10). Their waiting times are set on an average of 40 seconds. This results in a 30-second difference between the waiting times of low and high consistent traffic. The static TLC produces the highest waiting times followed by the actuated TLC. The lowest delays for vehicles are caused by the adaptive TLC algorithm.

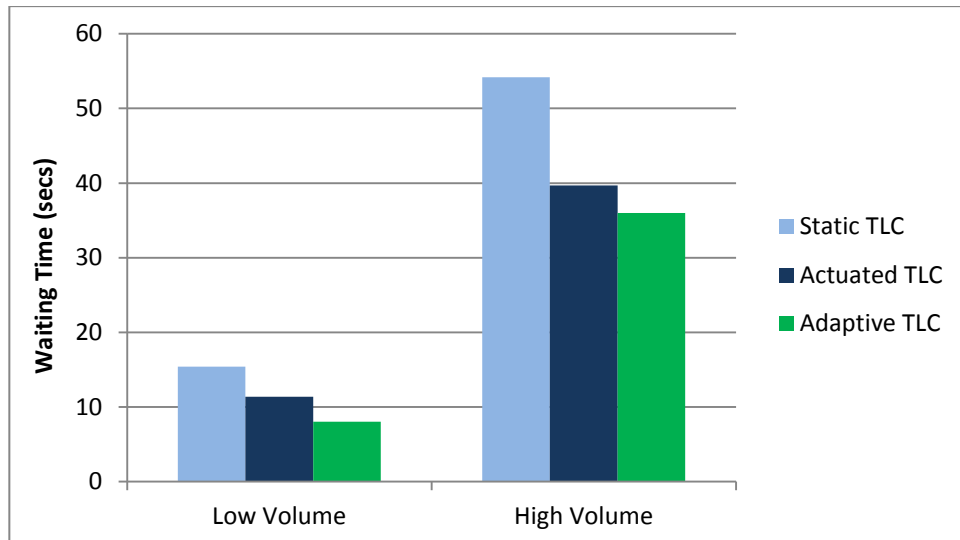


Figure 4.10 Average waiting time for consistent traffic conditions

The TLCs effect the travel times for the approaching lanes for each of the roads in the same way as the waiting time. Both are based on the order for reducing the duration a vehicles needs to move from the beginning of the simulated road to the end of the road which is also dubbed as the intersection, as shown in Figure 4.11. The difference here lays in the development between the low and high volume traffic samples as the average travel time is shorter for higher volumes. The maximum travel times for the high volume test cases generated by the actuated and adaptive TLC are 416 and 382 seconds total travel time, respectively. These values are higher in comparison to the low volume maxima of 363 and 344 seconds. The static TLC produces a maximum of over 450 seconds for the low volume samples and only 171 seconds for higher consistent traffic. While the maximum values are interesting, the average travel times from Figure 4.11 show that the average vehicle faces travel times below 20 seconds at all volumes.

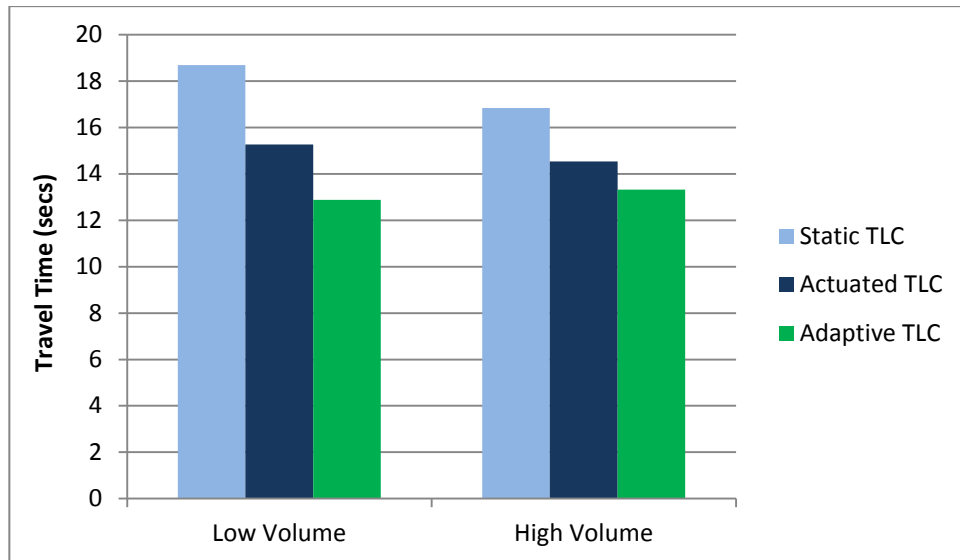


Figure 4.11 Average travel time for consistent traffic conditions

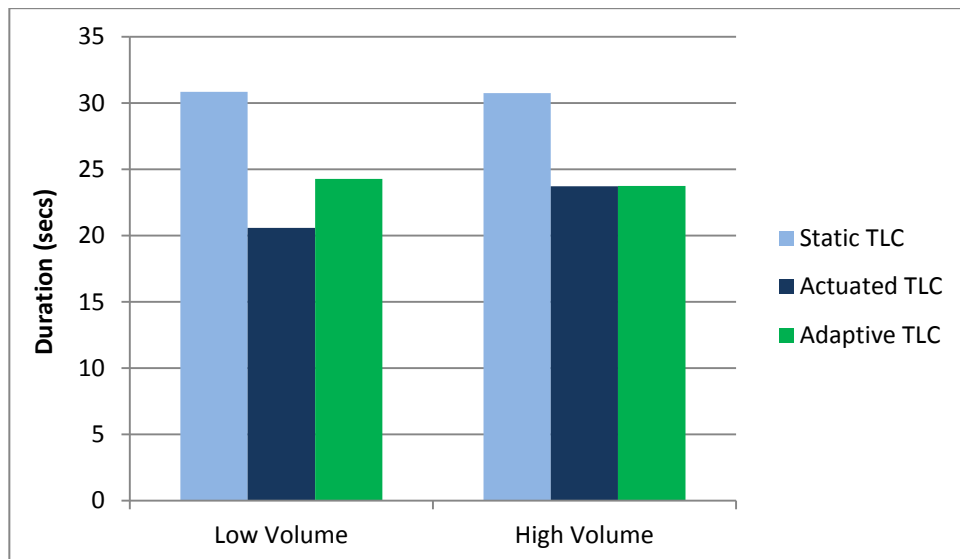


Figure 4.12 Average green phase duration for consistent traffic conditions

The waiting times and travel times rely on the traffic lights and their scheduling. While the green phase durations for the static TLC are set to a fixed time of 30 or 31 seconds, the average durations for the actuated and adaptive TLCs vary. The duration of the green phase increases for the actuated TLC from 20.5 seconds at low volume while the time for the adaptive TLC drops from 24.3 seconds. Both approaches have the duration of 23.7 seconds at high consistent traffic conditions.

4.5 Experiment 3: Variable Traffic Conditions over the timespan of one hour

4.5.1 Overview

In contrast to the consistent traffic conditions, this third experiment relates to the variations of throughput levels at the intersections Donore Avenue, Talbot St and Sean Mac Dermott St. Seven test cases are found for each intersection at the throughput analysis that have the time span of one hour and vary greatly in the approaching vehicle volumes. During the search and selection process of compelling cases three categories of varying traffic conditions can be established.

The first form is the increasing vehicle volumes with the condition that the throughputs increase rapidly within the chosen hour. The second group poses as the opposite approach by containing instances where the volumes fall significantly. Finally, the last category holds samples that have truly variable traffic conditions with alternating gradients for the volume development. Three test cases from each intersection fall into the increasing volumes. The remaining four samples from each intersection are divided equally to the second and third category with two each.

Table 4.1 Average volume for the categories of variable traffic conditions

Variable Category	Average Volume
Increasing Volume	247
Decreasing Volume	281
Alternating Volume	274

As shown in Table 4.1, the average volumes for the defined categories vary with a difference of approximately 30 vehicles reaching the intersection within each 15-minute block between the increasing volume and the other two groups. The average for the increasing volume is set at a throughput at 247 vehicles, whereas the decreasing volume and alternating volume is set at around 280 approaching vehicles in one interval of 15 minutes.

4.5.2 Results

With the three created categories, the results are divided on these test cases forming the groups of similar traffic conditions. There are three sections in this analysis concerning the waiting times for vehicles, travel times along the approaching roads and the green light phase durations.

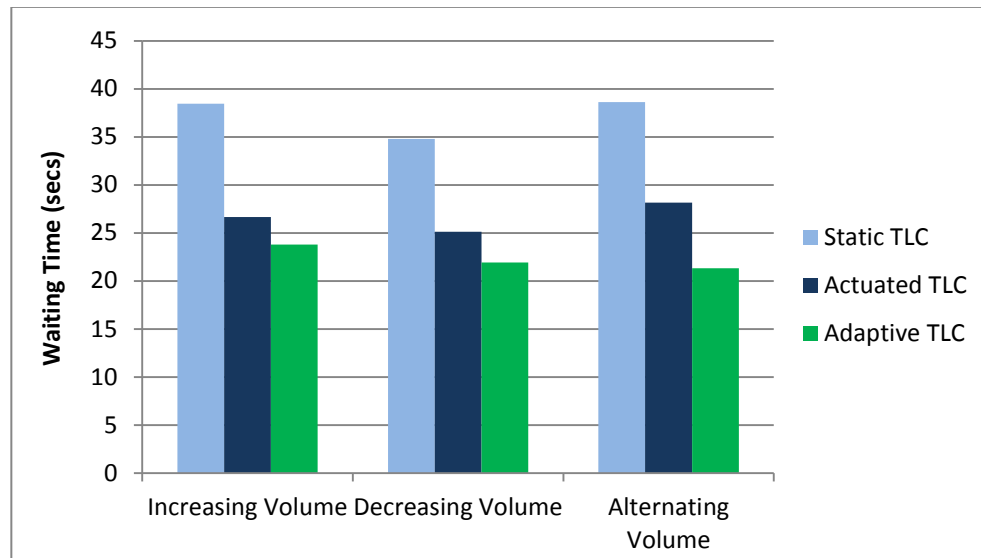


Figure 4.13 Average waiting time for variable traffic conditions

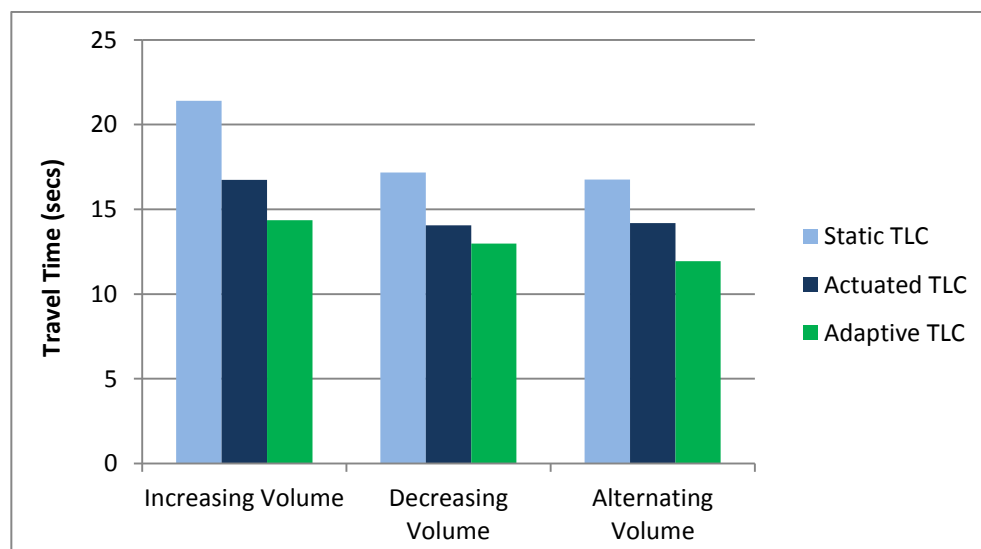


Figure 4.14 Average travel time for variable traffic conditions

Figure 4.13 shows the average delays for a vehicle approaching any of the three intersections. The first impression is that alternating volumes produce the longest waiting times for static and actuated TLCs. When the traffic volume decreases, the arising waiting time is lower than generated delays of the alternating throughput and the increasing volume. A static TLC produces the longest delays for vehicles, followed

by the actuated and the adaptive TLC. The difference between the delays of the static and the actuated TLC is 10 seconds for all variable traffic conditions. The discrepancy between the created stop times by actuated and adaptive TLC is smaller. Its value is the smallest for the category of increasing volume and the highest for the alternating volume.

Similar to the waiting times, the results for the average travel time per vehicle for the approaching roads of any of the intersections are the highest for the static TLC (see Figure 4.14). Following the static TLC is the actuated TLC and with the lowest travel time is the adaptive TLC. When the throughput volume of the intersection is increasing drastically, the highest travel times are produced. The difference to the decreasing and alternating volume categories is smaller than two seconds on average. It is therefore not considerably noticed by driver of the moving vehicle. The shortest average travel times are generated by the adaptive TLC ranging between twelve and fourteen seconds.

As shown in Figure 4.15, the average durations for the green light phases of the static and actuated traffic lights are very consistent across all three variable traffic condition groups at 30 and 22 seconds, respectively. This is standard for the static TLC as the times are fixed, but the actuated TLC can vary the length of the phase on the approaching vehicles. The comparison between the green light phases of adaptive TLC produces the results of calculating longer phases on average for the decreasing volumes and shorter phases when the volume is alternating.

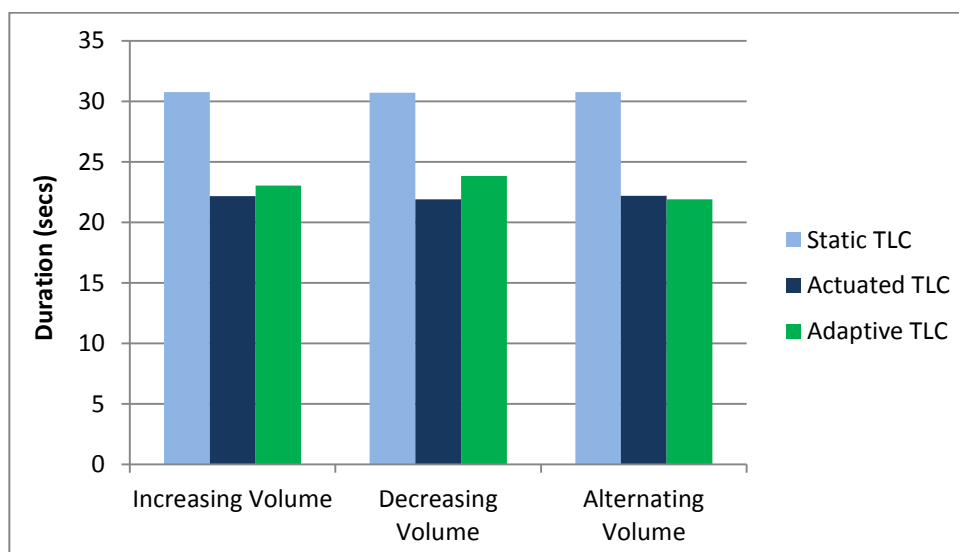


Figure 4.15 Average duration of green light phases for variable traffic conditions

4.6 Experiment 4: Day Simulations

4.6.1 Overview

As the day categories weekday, weekend and holiday influence the throughput of intersections in Dublin, the time span of a whole day is the foundation for the fourth experiment. An average daily development of the vehicle volumes passing all three intersections for each of the day categories is used for a final comparison between the three TLCs. The selected days are a rainy weekday, any holiday and any weekend day. The date span is the full six months of available input data. There are only 5 public holidays within these six months. Because of this condition, it is also applied to the other two test cases. The simulations were run on each intersection for all three days. This allows an inference on the average intersection in Dublin city.

4.6.2 Results

The day classification defines the groups for the analysis of the results. Similar to the experiments above the waiting times, travel times and the green light phase durations are used to compare the TLC approaches.

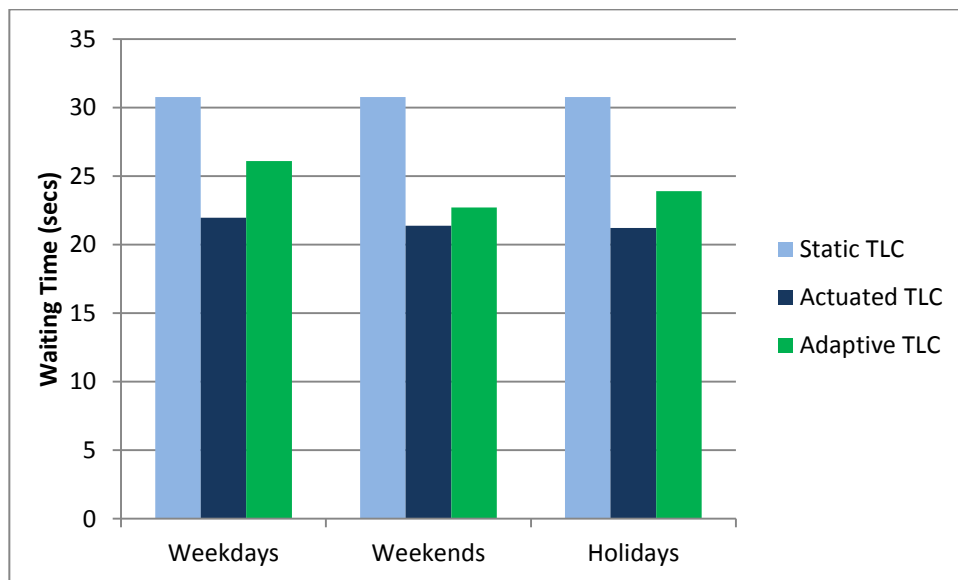


Figure 4.16 Average waiting time for the defined day categories weekdays, weekends and holidays

The average waiting times for weekdays are significantly higher than on weekends or holidays as shown in Figure 4.16. This difference is approximately 10 seconds for each of the TLCs. This is based on the higher traffic volumes detected on weekdays in the input data analysis of the detectors from Dublin City Council (see chapter 3.2.3). The

average throughput is also higher for weekends than holidays with an additional condition of more consistent traffic conditions. Holidays show the highest percentage of highly variable traffic conditions. There is also a 10 second difference between the static and actuated TLC and another 4 to 5 second discrepancy between the actuated and adaptive TLC.

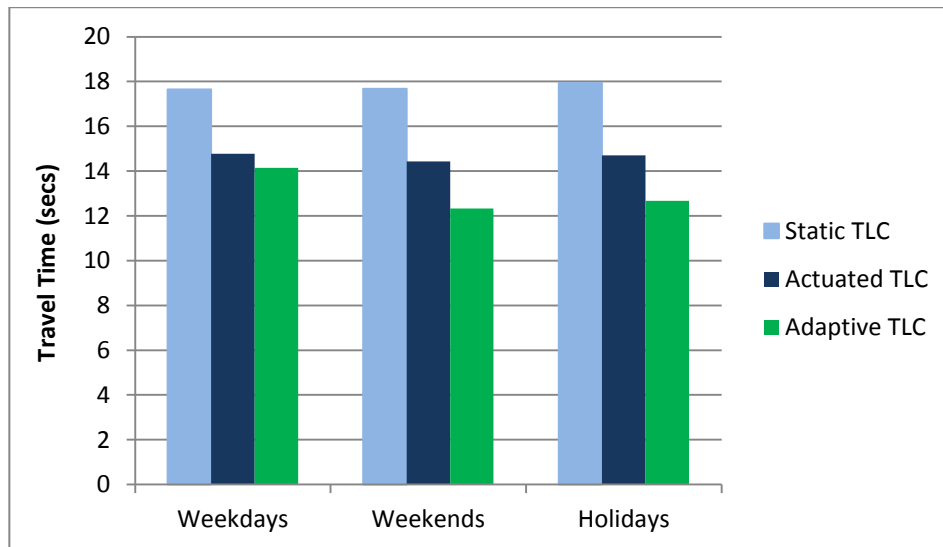


Figure 4.17 Average travel time for defined day categories weekdays, weekends and holidays

While the average waiting times produced by the TLCs for the days have different levels based on the throughput, the travel times do not show this discrepancy (see Figure 4.17). The static TLC produces travel times of just below 18 seconds for the vehicles on the approaching roads across all day forms. In the case of the actuated traffic light, the vehicles move slightly faster only taking about 14 seconds every day to travel along the roads leading to the intersection. There is only an alteration in travel times for the adaptively controlled traffic lights between weekdays and the other two groups. This means that on weekdays a vehicles needs 2 seconds longer on average to approach the intersection.

The slightly longer travel times for the adaptive TLC on weekdays are probably influenced by the longer green phase durations on these days with 26 seconds compared to the weekends and holiday samples with 22.7 and 23.9 seconds (see Figure 4.18). The duration of the green lights for the static TLC are consistently at just above 30 seconds. On weekdays the duration for the green phases determined by the actuated traffic lights are 0.5 seconds higher on average than on weekends and holidays.

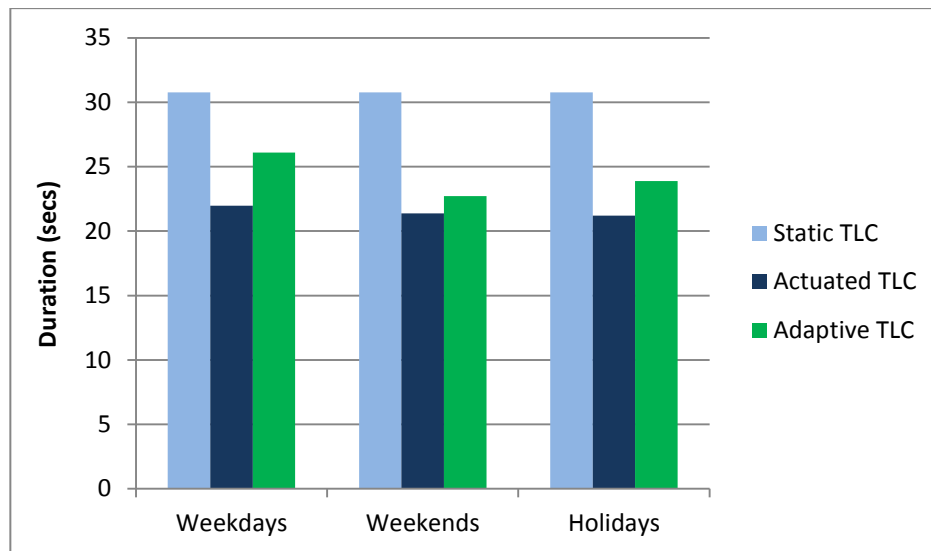


Figure 4.18 Average green light phase duration for defined day categories weekdays, weekends and holidays

4.7 Summary

The simulations conducted with the detector data from the DCC can represent the real traffic conditions existing in Dublin city. The comparison between the throughputs from Donore Avenue, Talbot Street and Sean Mac Dermott Street that are used for the input and the registered vehicles approaching the intersections in the SUMO network shows that the both throughput developments throughout the day are equal or very similar. This means that the data can be used without any additional conversion for the conducted experiments.

One of the first findings of these experiments is that the number of approaching vehicles influences the movement of vehicles together with the traffic light control. With increasing volumes the waiting times rise and the average speed of each vehicle falls. The waiting time for consistent traffic over a longer period of time as described in the second experiment is similar to the short-timed test case results with a light gain as the remaining vehicles at the stop line of the traffic lights are taken into account within the next 15-minute block and so on. This is not the case in Experiment 1 where only the vehicle volumes are tested within a short time span. The recorded waiting times in Experiment 3 with the varying traffic conditions show that decreasing volumes are closest to the results from the vehicle volume levels. When the volume levels vary more intensely in both directions, the waiting times produced by the traffic lights are higher. This stands in contrast to the fact that the average overall volume of samples from the varying traffic conditions is similar to the one from the decreasing

throughput. When the number of approaching vehicles increases rapidly, the recorded delays for vehicles are higher than the waiting times for the equal throughput level of 250 vehicles from Experiment 1.

As mentioned above the average speed of each vehicle reduces with the increasing number of vehicles approaching an intersection as the waiting times and the probability for stopping at a red light or at the end of the queue increase.

The travel times of vehicles approaching the intersections on the adjoining roads, while changing, do not vary considerably. Their averages only range within a time span of 12 and 19 seconds depending more on the TLC approach than the traffic volume. The vehicle journey times shorten slightly with higher volume levels. The reason behind this decline is not clear as the average vehicle speed drops and the waiting times rise for higher traffic volumes. This circumstance should increase the average travel time for a vehicle.

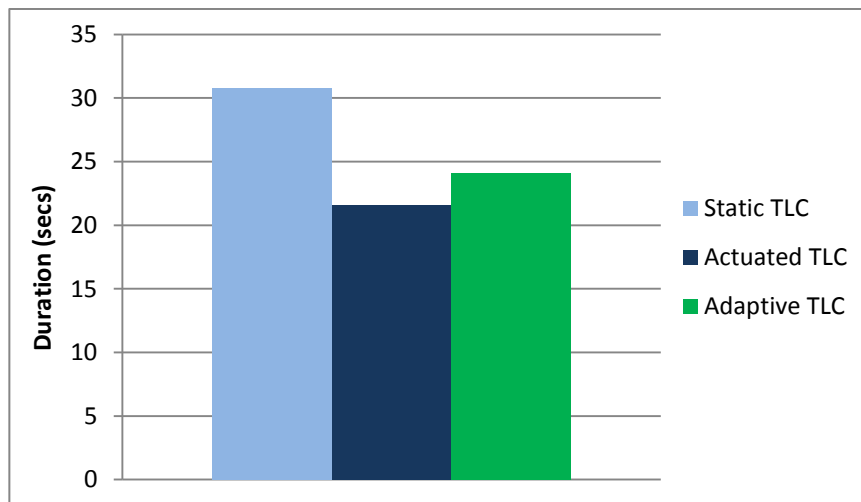


Figure 4.19 Overall average duration of green phases for an intersection in Dublin

The traffic light control and its schedule is the other major influence of the waiting times and travel times. The fixed traffic light system has its green phase durations set at an extent of 30 or 31 seconds depending on the intersection. The actuated traffic light determines its two main green phase durations based on the distance between the approaching vehicles with its average value ranging between 20 and 24 seconds.

The adaptive algorithm presented in this project produces green phase durations averaging between 21 and 25 seconds. The difference between the adaptive and the actuated TLC in the duration length is that the length of green phase for the actuated TLC increases with rising vehicle volumes, the duration computed by the adaptive

traffic light controller falls. Figure 4.19 shows the overall average duration of the three TLC approaches. The length of the green phase with the adaptive scheduling is slightly higher than the one of the actuated traffic light.

Overall, the adaptive TLC produces the best results in waiting times, vehicle speed and travel times across all four experiments, followed by the actuated in second place. The highest travel and waiting times plus lowest speeds are caused by the static traffic lights. The travel times, speed and waiting times are in some way corresponding to each other as the waiting time influences the speed of the approaching vehicles and therefore the travel time needed to reach the intersection. The waiting time in itself is affected by the number of approaching vehicles on a road and the phase duration and scheduling handled by the traffic light control mechanism.

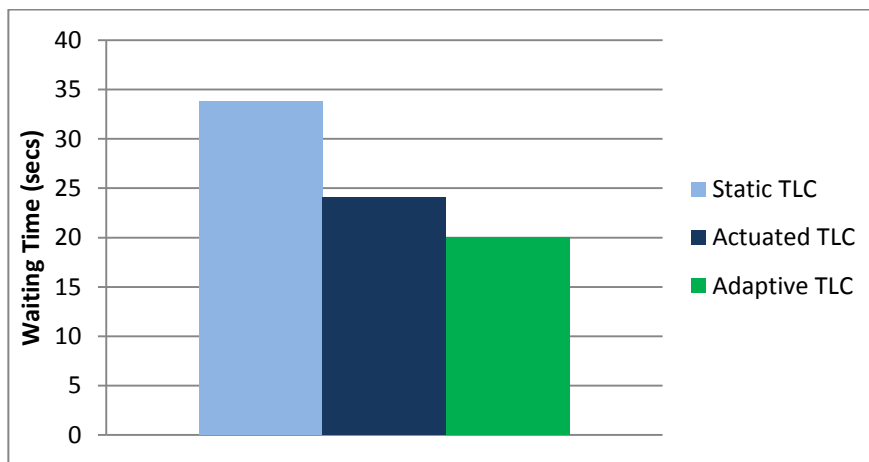


Figure 4.20 Average waiting time for TLC approaches in Dublin

Higher waiting times mean longer queues and more vehicles stopping at the traffic lights which in turn reduce the speed and increases the time needed to travel along the full length of the road. As shown in Figure 4.20, the adaptive TLC reduces the overall average waiting time from 33.82 seconds to 19.97 seconds which is an improvement of 41%. The adaptive TLC outperforms the actuated TLC by 17% in the generated waiting times. Actuated traffic lights shorten the waiting times by 29% compared to the static TLC.

5 DISCUSSION

5.1 Overview

This chapter discusses the work produced within this project described in the chapters above. It analyses the influences of traffic light control and traffic volume on the traffic conditions. This includes the data used, the developed adaptive traffic light control algorithm developed and the results. These points are assessed based on their significance to the defined hypotheses of this project, the acquired feedback from the DCC and state-of-the-art research in literature.

5.2 Use of Input Data

The data provided by the DCC represents nearly real-time data on the detected throughputs at selected intersections in Dublin. This is based on the circumstance that the DCC numerous utilises stop line detectors for data collection. The installed SCATS system provides this accumulated data in 15-minute intervals. The loop detectors detect any vehicle passing the sensor presenting an overall figure of all road traffic at an intersection.

Data used in similar projects are either generated vehicle volumes that do not rely on specific real world cases (Alabdallaoui et al., 2015; Djahel, Jabeur, Barrett, & Murphy, 2015; Younes et al., 2016) or positioning and journey data from buses and taxis (Daly et al., 2013; Gühnemann, Schäfer, Thiessenhusen, & Wagner, 2004; Protschky, Ruhhammer, & Feit, 2015) to estimate the traffic volume for the experiments and simulations conducted. While Bodenheimer et al. (2015) uses 3 hours of data from a ‘regular Monday’, it would be interesting to analyse and simulate the full potential of traffic conditions at intersections. Randomly generated traffic volumes can be indicators on the efficiency of a traffic light scheduling approach, but its results are not as adaptable to the real world as the simulations based on historic data for the vehicle counts from Dublin.

The analysis of the vehicle count data produced differences between the weekdays, weekends and holidays that is not simulated in the above cited literature but expected from experience at the DCC (O’Connor, 2016b). The weekdays show higher traffic and rapid transitions between low and high traffic levels in the mornings and evenings.

Contradicting this development, holidays and weekends have lower volumes throughout the day and the transitions between the lower and higher volume levels start later in the day with slower increases and decreases. The traffic conditions on holidays are more varying in detail compared to weekdays and weekends producing a jigsaw-like curve.

The rainfall data added to this study by providing the information that on holidays the volumes are generally lower and the afternoon peak time starts earlier on weekdays when it is raining. This information is used to evaluate the effectiveness of the tested traffic lights scheduling approaches. This comparison is not only based on vehicle volume levels and consistent traffic conditions, but also the variable traffic conditions found in the daily analysis.

Even though only three intersections are used in this project, the different volume levels, as described in 3.2.3, provide the evidence to use the data in the simulations and its results to be applicable for Dublin traffic conditions. Similar to found experimental environment in current research, only the throughput and approaching number of vehicles for the complete intersections are taken into account during the analysis and simulations. While there might also be differences between the vehicle volumes detected at different directions and times of the day, this information is not considered as important and necessary for this project at this stage. An example is the potential higher volume of vehicles streaming into a certain direction during morning peak time and another direction during evening peak time.

5.3 Adaptive Traffic Light Control

The proposed traffic light algorithm is truly adaptable to the approaching traffic. It uses minimal additional technology with one inductive loop installed in every lane of the road directions leading to the controlled intersection. This sensor measures the number of approaching vehicles that are particularly interested in the phase scheduling of the traffic lights. Based on the traffic volumes of the two directions, the green phase is either ended and switched to the other green phase or prolonged by a fraction of the default duration – that is twenty seconds. This provides the foundation to select the next green phase. It is based on the number of vehicles passing the loop sensors for each direction, since the time the phases have been selected last. To avoid confusion and miscalculation while determining the next green phase, the value of detected

vehicles for the chosen phase is reset to zero. This is a technique also used by Younes and Boukerche (2016) for their adaptive traffic light control.

Compared to the existing idea to evacuate less dense roads first (Mohamed et al., 2015), the proposed algorithm switches to or prolongs the roads with higher vehicle volumes. Another option would be based on the arrival time as described in the system setup of the Online Algorithm by Younes et al. (2016). The use of arrival times is not efficient with inductive loop technology. With the set distance of the sensor to the stop line, this information is not defined and would only be estimated.

The only software constraint for the TLC is the definition of minimum and maximum duration limits. These values of twenty and eighty seconds are chosen based on the given information on the split plans from the Dublin City Council and approaches in current research. The split plans for intersections vary in cycle length between 60 and 120 seconds (O'Connor, 2016a). Thus, the green light phases can have a duration between twenty and sixty seconds to include the amber phases and the green phases for the right-turning vehicles. While Li et al. (2016) support the view that a green light phase should not have a duration shorter than thirty seconds, the lower limit for this adaptive algorithm is set to twenty seconds. These limits could provide a possibility for further material for investigation, i.e. their influence on the waiting times of approaching vehicles. Increasing or decreasing the minimum and maximum values changes the allowed duration range for the green light phases of the traffic lights. This results in a possible change of effects for the approaching cars. The algorithm does not take the number of approaching cars during the last green phase for this direction and its duration into account to calculate the length of the newly determined phase.

The algorithm only uses two green light phases compared to four green phases in the static and actuated traffic light controls. This is on one hand caused by the demand for simplification and on the other hand based on the results found by Younes and Boukerche (2016). They found that fewer cycles provide shorter cycles meaning less waiting time. Two-phased scheduling approaches eliminate the requirement to determine the phase sequence. Either the existing phase is prolonged or a phase switch is necessary to the other green light phase. Depending on the number of used phases, this process can be rather complex as small changes in the approaching traffic can change the phase order (Bodenheimer et al., 2015).

The inductive loop sensors are positioned at a distance of 25 metres to the stop line and record the passing vehicles. While there is a comparison and analysis conducted for the location of the sensor in the approaching lanes of the roads to provide an overview of the influence it has on the productivity of the TLC, this research could be more extensive. The analysis of the waiting times is evaluates the different forms of the proposed algorithms when detecting vehicles. This information is needed for the experiments with the vehicle volumes and traffic conditions, but only to the extent presented in this context. Using multiple kinds of sensors would also make the TLC system more ‘intelligent’, while also providing more information on the traffic conditions for the decisions performed by the algorithm. An example for this would be the use of messages from vehicles using VANET technology (Barba et al., 2012; Hancke et al., 2012).

According to feedback from the DCC (O’Connor, 2016b), a TLC system, which is 100% adaptive, does not exist in the real world as user specifications and conditions need to be fulfilled and therefore implemented into a traffic light management system. One case that is mentioned within this feedback is the demand for fixed durations of green phases at a certain time of the day based on found traffic analysis.

Additionally, there might also be some offset that needs to be set and defined, when multiple intersections are adjoined into a network. This is based on the idea of linking the control of intersections to achieve a process called the ‘green wave movement’, that is also used in TRANSYT (Robertson & Bretherton, 1991) and in the multi-agent system proposed by Rakkesh et al. (2015).

5.4 Results

5.4.1 Hypotheses

The experiments are not specifically associated to the defined hypothesis. This section aims to discuss the results of the experiments based on the constructed hypothesis. The null hypothesis underlying this project is as follows:

Hypothesis 0: The proposed adaptive traffic light algorithm can handle the approaching traffic conditions better than static and actuated traffic light scheduling.

The results from all experiments show that the adaptive TLC produces the shortest waiting times for the approaching vehicles of an intersection. The actuated TLC has the medium levelled waiting times followed by the static traffic lights with the highest delays. This is unrelated to the number of vehicles approaching an intersection controlled by the traffic light control mechanisms. The biggest differences between the waiting times of the three TLC mechanisms are during the time periods, when the traffic conditions are extremely varying. This circumstance occurs more often than consistent traffic conditions over a longer time period. As it can be found in the input data analysis, there are not only volume differences between the day categories, but also contrasting throughput levels for an intersection in Dublin throughout one day (see chapter 3.2.3). The speed of vehicles approaching the traffic lights is increased by the adaptive TLC compared to the average speed produced by the actuated and static traffic lights as shown in Experiment 1.

The average speed is also part of the first hypothesis created with the additional of traffic volume:

Hypothesis 1: The average speed of approaching vehicles falls with increasing traffic volume levels.

A higher traffic volume means that more vehicles are approaching and want to cross the intersection slowing down the vehicles. Experiment 1 with the vehicle volumes covers this hypothesis by analysing the results of the average speed based on the volume levels. As defined in the hypothesis, the speed for a vehicle approaching an intersection drops when the throughput increases from 50 to 400 vehicles per 15-minute interval. This decrease is not as extreme as expected with only 2 km/h across all volume levels. The speed for every TLC approach is below 30 km/h even though the maximum allowed speed for all roads approaching any of the three simulated intersections in Dublin is defined with 50 km/h. This can be explained with the number of waiting and decelerating vehicles and the fact that the possibility of a vehicle moving at full speed throughout the whole distance to the intersection is quite low.

The traffic volume can not only impact the average vehicle speed, but also the waiting and travel times of vehicles. This is the content of the second hypothesis.

Hypothesis 2: The waiting and travel times for approaching vehicles rise with increasing traffic volume levels.

The results from the Experiment 1 show that the waiting times increase immensely for higher volumes compared to low volume levels. For the static TLC this development is a multiplication of the waiting time by 8. The waiting time at a high volume for the adaptive TLC is only 400% of the generated waiting time at fifty vehicles approaching the intersection.

In contrast to this, the travel times do not increase at all for higher volume levels but fall slightly instead. This does not reflect the created Hypothesis 2 and the results of longer waiting times and lower speed for high traffic volume levels. Longer waiting times for the approaching roads and lower speed would suggest a longer travel time.

The last hypothesis is founded on the assumption discovered during the literary research on the phase durations and the resulting cycle time.

Hypothesis 3: Shorter green light phase durations produce shorter waiting times.

This hypothesis also finds its foundation and link to the main hypothesis in way, that across all experiments the average phase durations are the longest for the static TLC followed by the adaptive and the actuated TLC with the shortest phase durations. The static TLC has an average phase duration of 30.7 seconds. The adaptive TLC algorithm calculates its phase lengths between 20 and 80 seconds with an average of 24 seconds. The actuated traffic lights mechanism can determine the green phase durations between 20 and 60 seconds with the average length of 21.6 seconds (see Figure 4.19). In contrast to this, the waiting times are the shortest for the adaptive TLC algorithm, followed by the actuated and static TLCs (see Figure 4.20). This means that shorter phases influence the resulting waiting times, but are not the deciding factor.

5.4.2 Comparison with current State-of-the-Art Results

This section aims to discuss the results from the experiments with regard to the results found in current research. These are state-of-the-art research projects that compare different traffic light approaches on traffic conditions.

A first thing that needs to be mentioned is that the results for average waiting times cannot be compared directly based on their values. The waiting times used in this project are defined as the sum of seconds within a specified period of time when a vehicle is stopped on an approaching road of the intersection. In the found literary research the variable *waiting times* stands for the average waiting time per vehicle.

To approximate these waiting times of individual vehicles as best as possible, the time interval for the output of information on the edge-based data from the simulation is set to sixty seconds. This output option holds the waiting time information. This means that the waiting times found in this project should generally be higher than the average waiting times of an individual vehicle. Due to this circumstance, the following comparison is based on the calculated percentages between the TLC approaches from the summary (see chapter 4.7).

The two most similar projects to this are comparing adaptive, actuated and static TLC approaches. They are set based on wireless sensor networks or a multi-agent system for their system approaches.

The first one by Zhou et al. (2010) proposes an adaptive algorithm that provides the lowest vehicle waiting times compared to the other two TLC strategies similar to the results found here. The experiments use traffic density on the roads approaching the controlled intersection instead of traffic volume and the waiting times for the static traffic lights differ drastically from the waiting times found with this static TLC. While there is a difference between the static, actuated and adaptive TLCs in both projects, the waiting time for the static TLC in the experiments from Zhou et al. increases rapidly for higher densities to a delay of multiple minutes on average. The waiting time in this project stays below 80 seconds even for the highest volume level.

The multi-agent system approach analyses the proposed traffic light control with single agents called Soilse by comparing its results to a static and SAT approach with the latter being similar to the functionality of the SCATS system. It has the same scheduling strategy as the mentioned actuated traffic light control. It also uses traffic conditions from Dublin for its experiments (Salkham & Cahill, 2010). The Soilse control strategy provides shorter waiting times for vehicles by nearly 90% and around 30% compared to the static and the SCATS-based traffic light scheduling. According to Salkham and Cahill, the SAT algorithm experiences higher difficulties dealing with varying traffic conditions compared to the Soilse approach. This is similar to the greater differences found in this project for the experiment with varying traffic conditions.

While Xiao et al. (2015) only analyses an adaptive and static TLC for the resulting waiting times, the input data used for the experiments is the number of approaching vehicles for an intersection. This is equal to the experiments conducted here and also

provides the analysis on the specific volume levels. The difference between the adaptive and static TLC is more substantial with 75% compared to the 41% found in this project. The waiting times increase in both projects with higher volumes approaching the intersection with similar increases compared to the drastic increase found by Zhou et al. (2010).

A genetic algorithm proposed by Fujdiak et al. (2015) with its comparison to a static TLC approach generates similar differences between the static and adaptive scheduling systems. Small differences in average waiting time for an approaching vehicle can be found for lower volumes in both experiments. For higher volumes the genetic algorithm produces 36% fewer delays for vehicles to the static traffic lights compared to 41% for this proposed adaptive TLC algorithm. The division for the volume levels used in the experiments with the genetic algorithm are based on the definition of a 100% traffic conditions status. This causes the low volume levels for the conducted experiments by Fujdiak et al. (2015) to be slightly higher compared to the low volume level of fifty approaching cars for an intersection.

While the waiting times cannot be compared directly to the results of current state-of-the-art research, the differences between the waiting times provide a basis for the discussion. The average speed and travel times are not comparable to other found literary research, because most projects concentrate on the minimisation of waiting times for vehicles. They therefore do not present results containing the influence of the analysed traffic lights on the travel times and speed for vehicles.

5.5 Summary

This chapter discusses the input data, the proposed adaptive TLC algorithm and the results with regard to the hypotheses and current state-of-the-art research. It is found that the use of simulation input data from the real world is not common in similar projects. Traffic volumes on the other hand are used for the experiments and evaluation of traffic light control approaches.

The proposed TLC algorithm and its results prove to be competitive to similar state-of-the-art research. The TLC only uses loop detectors for collecting the data on the vehicle volumes compared to the more advanced approaches with VANET or advanced sensing. The results show that this dynamic scheduling mechanism can reduce waiting times in similar manner to these projects.

While most of the hypotheses prove to be valid by the experiments, including the null hypothesis, there are two exceptions. One half of the second hypothesis with the focus on the travel times increasing for high vehicle volume levels proves to be wrong as the results from the experiments show that the travel times decrease slightly for higher volume levels. Moreover, the third hypothesis is also found to be not true by the conducted experiments. Shorter phases do not mean shorter waiting times in a general circumstance.

6 CONCLUSION

6.1 Research Overview

Traffic management presents to be one of the critical challenges for growing city areas around the world. There is a need to make the management of traffic light control more advanced to the level of it being a ‘smart’ technological system. This not only reduces traffic congestion and delays for vehicles, but can also reduce the CO₂ emissions. There are several advances to provide a system that can adapt to the existing traffic conditions dynamically. This approach can be defined as an adaptive traffic light control. Current research uses information from cameras, inductive loops, social media and the idea of VANET with vehicles that can communicate with each other and infrastructure to measure the approaching traffic.

Dublin as the Irish capital uses one of the most popular management systems for controlling the traffic light schedule called SCATS. The DCC has inductive loops installed at the stop lines at numerous intersections in the city centre of Dublin detecting passing vehicles and providing the volume data at a set interval for analysing purposes.

6.2 Problem Definition

Dublin as a city with the concept of becoming smarter in its management presents an ideal place to use real-world data from the SCATS system for the research on traffic light control. Most research projects use automatically created data for the evaluation of TLCs. Moreover, the sensor technologies for detecting traffic conditions in current research are rather complex with the implementation costs and challenge of trusting a source medium. An alternative idea is to use inductive loops with the possibility to adopt the already existing sensors installed in Dublin for later realisation.

Based on this information, the main intention of this project is to evaluate traffic light control approaches in simulations based on real-world data. An adaptive traffic light control algorithm is proposed within this project using inductive loops as sensors for measuring traffic volume to make the traffic light management more intelligent. It is then compared to the two other main approaches for traffic light management: static and actuated.

6.3 Design, Experiments and Results

6.3.1 Design

The analysis of the vehicle count data from the Dublin City Council is on a six-month period of 2016 from three intersections positioned in Dublin. The intersection throughputs portray different volume levels providing the ground for justification of using the data from these intersections for the analysis of an average intersection in Dublin. The analysis of this input data shows that there is a difference between the day categories weekdays, weekends and holidays in the development of the traffic volume throughout the day. Added rainfall data does not provide as much impact as expected on the daily development of traffic volumes. The biggest difference between rainy and dry days can be found for holidays.

The comparison between the static, actuated and adaptive TLCs is the framework for the experiments. The adaptive algorithm uses two green phases that represent the two main green light phases for the static and actuated traffic light program. These two phases stand for the directions North-South and East-West of the approaching roads. The static and actuated traffic lights have additional phases for right-turning vehicles. This is similar to the traffic light program found in the used SCATS system at the DCC. The optimal location for the inductive loops is at a distance of 25 metres to the intersection, as found in an analysis on the positioning of the sensors.

An additional software tool is designed and implemented with the C++ library Qt to automate the simulation process with all three TLC approaches. This tool converts the input data from the DCC into a format that can be used by the simulation tool SUMO for the moving vehicles. It also runs the simulations and prepares the generated output data for further analysis by converting the XML files into CSV files.

6.3.2 Experiments

The experiments conducted to analyse the effectiveness and influence of the traffic light controls on the traffic flow are divided in the used time spans and the type of traffic conditions. A first experiment is conducted to compare the traffic lights based on the volume levels within a short interval of fifteen minutes. The next two experiments have a time span of one hour covering consistent and varying traffic conditions. The last experiment compares the different day categories in a full day

simulation as the daily developments are varying from each other. The weekday has the highest volumes and the most dramatic increases and decreases based on the difference between day and night time. A holiday has the most varying traffic conditions with volume rises and falls throughout the whole day but similar volume levels to the weekend.

6.3.3 Results and Evaluation

The evaluation of vehicle counts from the input data with the detected volumes from the inductive loops installed in the simulated roads in SUMO is created. It shows that the real-world data can be used in the simulations without any transformation to simulate the traffic conditions existing in Dublin in the experiments.

The proposed adaptive traffic light algorithm produces the shortest waiting times in all experiments. It is followed by the actuated and finally the static traffic light control approaches. The waiting times increase for rising traffic volume levels. While the rise for the adaptive and actuated traffic light control is quite slow, the waiting times for a static scheduling is more accelerated. Consistent and varying traffic conditions over a longer time period behave in a similar way to the corresponding vehicle volume levels with the short time span of fifteen minutes. Rapidly increasing traffic volume provides the only generated higher waiting time compared to consistent traffic conditions at the same level.

The found average differences between the traffic light control approaches are similar to the results from state-of-the-art research. The main difference found in the comparison with other results is that the comparison proves to be quite difficult. The definition for the measures *waiting time* and *volume* used in this and other current projects differ from each other. To circumvent this fact, the differences between the approaches are measured in percentages to allow comparison as other researches also use this method of percentages for evaluation. The adaptive TLC reduces the waiting time by 41% compared to the static TLC and by 17% to the actuated TLC, while having an average duration for the green light phases of 24 seconds.

6.4 Contributions and Impact

The main contribution of this work is the detailed analysis of the generated influence of different traffic light control strategies on traffic conditions existing in Dublin city. This is caused by the use of real-world data for the performed simulations in the experiments and no major discrepancies found between the detected vehicle counts of the DCC and the loop sensors used within the simulations.

The input data analysis shows that there is a difference in volume levels and daily development between the day categories weekday, weekend and holidays. This presents a point that should be included when testing the performance and effectiveness of a traffic light control approach. In contrast to this, the rainfall data does not provide a prominent change in the results of the daily development of intersection throughput.

Moreover, this thesis proposes an adaptive traffic light control algorithm with the aim to enhance traffic flow by changing the traffic lights dynamically. This includes the reduction of waiting time and increase of speed by adapting the green light phases to the number of approaching vehicles. Another focus of the algorithm design is the simplification of the traffic light program with only two green light phases for the intersection. It also uses inductive loop sensors as only source for the information on traffic conditions.

Finally, as the DCC uses the SCATS system to manage the traffic lights in Dublin city, its approach can be seen as similar to the defined actuated traffic light control. While there is room for improvement to a more adaptive and intelligent traffic light control strategy, it provides better results than a purely static traffic light schedule with fixed-time phase durations.

6.5 Future Work

6.5.1 Extending Input Data Volume

The vehicle count data from the DCC is only limited to three intersections and six months. Data from more intersections in the inner and outer city centre of Dublin are helpful to provide more insight into the traffic conditions of Dublin and a more detailed view of the generated traffic from the simulated traffic light management strategies. The time period of collected vehicle counts could be extended to a longer

time span than six months. A suggestion would be the use of one year of data for the detected vehicle counts. This provides a higher number of state holidays. A request for the number of holidays - that is five days - with the requirement of a rainy day returns one single record that meets both conditions. A larger dataset would provide a broader view to this inquiry.

The use of direction-specific data might be an interesting point to analyse and simulate with the traffic light scheduling approaches. Morning and afternoon peak times can cause traffic flows in specific directions. This work only uses the sum of the detected vehicles for one 15-minute interval as the throughput of the intersection for that period. This results in the assumption that the number of approaching vehicles is the same on average for each adjoining road. This is not the reality in the detected traffic conditions. Including these diversities in volumes approaching from each road into the experiments might provide another angle for the evaluation of the traffic lights.

Moreover, while only actual rainfall data is used for this analysis, weather forecast information might provide another view point on the influence of weather on the traffic conditions.

6.5.2 Fine-tuning the Adaptive Traffic Light Control Algorithm

The proposed algorithm for an adaptive traffic light control needs some more testing and further calibration. The two main areas are the algorithm itself and the location of the used sensors.

The algorithm could be tested on the definition of the duration range. This could be calibrated to the optimal minimum and maximum limits. The limits set in this work are based on the found knowledge of the best dimension in current state-of-the-art research. It could be extended and reduced, while analysing and comparing the consequences on the traffic flow variables waiting time, speed and travel time. Additionally, when calculating the number of vehicles approaching the intersection associated for the green light phases, the maximum number of vehicles from one direction can be used instead of the sum of both numbers. This is based on the assumption that given the example of 5 vehicles at the northern road and 3 vehicles at the southern road, the three vehicles should be able to pass the intersection, if the duration of the green phase is optimised for five vehicles.

The positioning of the loop sensor in the road at the optimal distance to the traffic lights can help with the efficiency of the traffic light control strategy. While there is an analysis on this area in this thesis, a more thorough evaluation of the position and its influence can elevate performance of the traffic light control algorithm.

6.5.3 Experiments on a large Scale

This work only provides a test of the performance of the traffic light control approaches for individual intersections. While the adaptive TLC algorithm shows positive results in these experiments, the next step is to widen the scale of the experiments. Multiple intersections should be used as basis for a comparison and evaluation. In a first step, this network should represent a distributed system with separately working traffic light controls. The second step is the process of ‘linking’ intersections by enabling some form of communication between the controllers of adjoining intersections. This means that the controller with the adaptive TLC algorithm can communicate with neighbouring intersections to promote the ‘green wave’ movement. This can be described as the process of allowing a specific amount of vehicles to ‘flow’ through a set collection of intersections without stopping. This is based on the condition, that the green light phases have offsets to evacuate these vehicles from the road section.

BIBLIOGRAPHY

- Alabdallaoui, S., Berraissoul, A., & Idboufker, N. (2015). Performance evaluation of RED approach for traffic lights management. In *2015 15th International Conference on Intelligent Systems Design and Applications (ISDA)* (pp. 358–362). <https://doi.org/10.1109/ISDA.2015.7489254>
- Al-Khateeb, K., & Johari, J. A. Y. (2008). Intelligent dynamic traffic light sequence using RFID. In *International Conference on Computer and Communication Engineering, 2008. ICCCE 2008* (pp. 1367–1372). <https://doi.org/10.1109/ICCCE.2008.4580829>
- Artikis, A., Weidlich, M., Schnitzler, F., Boutsis, I., Liebig, T., Piatkowski, N., ... Gunopulos, D. (2014). Heterogeneous stream processing and crowdsourcing for urban traffic management. In *In Proceedings of the 17th International Conference on Extending Database Technology*.
- Barba, C. T., Mateos, M. Á., Soto, P. R., Mezher, A. M., & Igartua, M. A. (2012). Smart city for VANETs using warning messages, traffic statistics and intelligent traffic lights. In *2012 IEEE Intelligent Vehicles Symposium (IV)* (pp. 902–907). <https://doi.org/10.1109/IVS.2012.6232229>
- Bodenheimer, R., Eckhoff, D., & German, R. (2015). GLOSA for adaptive traffic lights: Methods and evaluation. In *2015 7th International Workshop on Reliable Networks Design and Modeling (RNDM)* (pp. 320–328). <https://doi.org/10.1109/RNDM.2015.7325247>
- Bretherton, D., Bodger, M., & Baber, N. (2004). SCOOT - the future [urban traffic control]. In *12th IEE International Conference on Road Transport Information and Control, 2004. RTIC 2004* (pp. 301–306). <https://doi.org/10.1049/cp:20040045>
- Covell, M., Baluja, S., & Sukthankar, R. (2015). Micro-Auction-Based Traffic-Light Control: Responsive, Local Decision Making. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems* (pp. 558–565). <https://doi.org/10.1109/ITSC.2015.98>
- Daly, E. M., Lecue, F., & Bicer, V. (2013). Westland Row Why So Slow?: Fusing Social Media and Linked Data Sources for Understanding Real-time Traffic Conditions. In *Proceedings of the 2013 International Conference on Intelligent*

- User Interfaces* (pp. 203–212). New York, NY, USA: ACM.
<https://doi.org/10.1145/2449396.2449423>
- Dissanayake, D. T., Senanayake, S. M. R., Divarathne, H. K. D. W. M. M. R., & Samaranyake, B. G. L. T. (2009). Real-time dynamic traffic light timing adaptation algorithm and simulation software. In *2009 International Conference on Industrial and Information Systems (ICIIS)* (pp. 563–567).
<https://doi.org/10.1109/ICIINFS.2009.5429797>
- Djahel, S., Doolan, R., Muntean, G. M., & Murphy, J. (2015). A Communications-Oriented Perspective on Traffic Management Systems for Smart Cities: Challenges and Innovative Approaches. *IEEE Communications Surveys Tutorials*, 17(1), 125–151. <https://doi.org/10.1109/COMST.2014.2339817>
- Djahel, S., Jabeur, N., Barrett, R., & Murphy, J. (2015). Toward V2I communication technology-based solution for reducing road traffic congestion in smart cities. In *2015 International Symposium on Networks, Computers and Communications (ISNCC)* (pp. 1–6). <https://doi.org/10.1109/ISNCC.2015.7238584>
- Dotoli, M., Fanti, M. P., & Meloni, C. (2006). A signal timing plan formulation for urban traffic control. *Control Engineering Practice*, 14(11), 1297–1311.
<https://doi.org/10.1016/j.conengprac.2005.06.013>
- Fujdiak, R., Misurec, J., Mlynek, P., & Petrak, T. (2015). Verification of genetic algorithm in dynamic traffic light management. In *2015 38th International Conference on Telecommunications and Signal Processing (TSP)* (pp. 314–318).
<https://doi.org/10.1109/TSP.2015.7296275>
- Gao, K., Zhang, Y., Sadollah, A., & Su, R. (2016). Optimizing urban traffic light scheduling problem using harmony search with ensemble of local search. *Applied Soft Computing*, 48, 359–372.
<https://doi.org/10.1016/j.asoc.2016.07.029>
- Gasparini, L., Bouillet, E., Calabrese, F., Verscheure, O., O'Brien, B., & O'Donnell, M. (2011). System and analytics for continuously assessing transport systems from sparse and noisy observations: Case study in Dublin. In *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)* (pp. 1827–1832). <https://doi.org/10.1109/ITSC.2011.6082982>
- Gühnemann, A., Schäfer, R.-P., Thiessenhusen, K.-U., & Wagner, P. (2004). *Monitoring Traffic and Emissions by Floating Car Data* (Berichtsreihe). Retrieved from <http://elib.dlr.de/6675/>

- Guo, H., Jiang, G., & Zhu, W. (2007). Study on Identification Method for Urban Road Traffic Conditions with Inductive Loop Data. In *2007 IEEE International Conference on Automation and Logistics* (pp. 1736–1740).
<https://doi.org/10.1109/ICAL.2007.4338853>
- Hancke, G. P., Silva, B. de C. e, & Hancke, J. (2012). The Role of Advanced Sensing in Smart Cities. *Sensors*, *13*(1), 393–425. <https://doi.org/10.3390/s130100393>
- Hu, W., Wang, H., Yan, L., & Du, B. (2015). A Hybrid Cellular Automaton Mechanism Inspired Approach for Dynamic and Real-Time Traffic Lights Scheduling. In *2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom)* (pp. 105–112).
<https://doi.org/10.1109/UIC-ATC-ScalCom-CBDCCom-IoP.2015.39>
- IBM. (2013, September 9). IBM - Dublin City Council Case Study [CT831]. Retrieved December 29, 2016, from
<http://www.ibm.com/software/businesscasestudies/hu/hu/corp?synkey=P468392F62276C24>
- Kanungo, A., Sharma, A., & Singla, C. (2014). Smart traffic lights switching and traffic density calculation using video processing. In *Engineering and Computational Sciences (RAECS), 2014 Recent Advances in* (pp. 1–6).
<https://doi.org/10.1109/RAECS.2014.6799542>
- Keyarsalan, M., & Ali Montazer, G. (2011). Designing an intelligent ontological system for traffic light control in isolated intersections. *Engineering Applications of Artificial Intelligence*, *24*(8), 1328–1339.
<https://doi.org/10.1016/j.engappai.2011.03.005>
- Köhler, E., & Strehler, M. (2012). Combining Static and Dynamic Models for Traffic Signal Optimization Inherent Load-dependent Travel Times in a Cyclically Time-expanded Network Model. *Procedia - Social and Behavioral Sciences*, *54*, 1125–1134. <https://doi.org/10.1016/j.sbspro.2012.09.827>
- Krajzewicz, D., Hertkorn, G., Rössel, C., & Wagner, P. (2002). SUMO (Simulation of Urban MObility) - an open-source traffic simulation. In A. Al-Akaidi (Ed.), *Proceedings of the 4th Middle East Symposium on Simulation and Modelling (MESM20002)* (pp. 183–187). Sharjah (United Arab Emirates). Retrieved from
<http://elib.dlr.de/6661/>

- Lazaroiu, G. C., & Roscia, M. (2012). Definition methodology for the smart cities model. *Energy*, 47(1), 326–332. <https://doi.org/10.1016/j.energy.2012.09.028>
- Lécué, F., Tallevi-Diotallevi, S., Hayes, J., Tucker, R., Bicer, V., Sbodio, M., & Tommasi, P. (2014). Smart traffic analytics in the semantic web with STAR-CITY: Scenarios, system and lessons learned in Dublin City. *Web Semantics: Science, Services and Agents on the World Wide Web*, 27–28, 26–33. <https://doi.org/10.1016/j.websem.2014.07.002>
- Li, J., Zhang, Y., & Chen, Y. (2016). A Self-Adaptive Traffic Light Control System Based on Speed of Vehicles. In *2016 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C)* (pp. 382–388). <https://doi.org/10.1109/QRS-C.2016.58>
- McGoldrick, P. (2016, July 12). Traffic Light Control in Dublin Outer Areas and Limerick - Traffic Solutions [Telefon].
- Miz, V., & Hahanov, V. (2014). Smart traffic light in terms of the cognitive road traffic management system (CTMS) based on the Internet of Things. In *Design Test Symposium (EWDTS), 2014 East-West* (pp. 1–5). <https://doi.org/10.1109/EWDTS.2014.7027102>
- Mohamed, B. A., Abderrahim, G., Anouar, B., Mohammed, B., & Kaoutar, B. A. (2015). Dynamic Traffic Light Control for Intelligent Mobility in Smart Cities. *Journal of Theoretical and Applied Information Technology*, 73(2), 261–268.
- Möller, D. P. F., Fidencio, A. X., Cota, E., Jehle, I. A., & Vakilzadian, H. (2015). Cyber-physical smart traffic light system. In *2015 IEEE International Conference on Electro/Information Technology (EIT)* (pp. 546–551). <https://doi.org/10.1109/EIT.2015.7293395>
- O'Connor, A. (2016a, July 18). Dublin City Council - Traffic light Control in Dublin City and SCATS.
- O'Connor, A. (2016b, December 16). Feedback on Results of Duclín City Traffic.
- Protschky, V., Ruhhammer, C., & Feit, S. (2015). Learning Traffic Light Parameters with Floating Car Data. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems* (pp. 2438–2443). <https://doi.org/10.1109/ITSC.2015.393>
- Rakkesh, S. T., Weerasinghe, A. R., & Ranasinghe, R. A. C. (2015). Traffic light optimization solutions using multimodal, distributed and adaptive approaches. In

- 2015 Fifteenth International Conference on Advances in ICT for Emerging Regions (ICTer) (pp. 220–225). <https://doi.org/10.1109/ICTER.2015.7377692>
- Robertson, D. I., & Bretherton, R. D. (1991). Optimizing networks of traffic signals in real time-the SCOOT method. *IEEE Transactions on Vehicular Technology*, 40(1), 11–15. <https://doi.org/10.1109/25.69966>
- Salkham, A., & Cahill, V. (2010). Soilse: A decentralized approach to optimization of fluctuating urban traffic using Reinforcement Learning. In *2010 13th International IEEE Conference on Intelligent Transportation Systems (ITSC)* (pp. 531–538). <https://doi.org/10.1109/ITSC.2010.5625145>
- Sims, A. G., & Dobinson, K. W. (1980). The Sydney coordinated adaptive traffic (SCAT) system philosophy and benefits. *IEEE Transactions on Vehicular Technology*, 29(2), 130–137. <https://doi.org/10.1109/T-VT.1980.23833>
- Srivastava, J. R., & Sudarshan, T. S. B. (2013). Intelligent traffic management with wireless sensor networks. In *2013 ACS International Conference on Computer Systems and Applications (AICCSA)* (pp. 1–4). <https://doi.org/10.1109/AICCSA.2013.6616429>
- Suthaputchakun, C., & Sun, Z. (2015). A Novel Traffic Light Scheduling Based on TLVC and Vehicles #x2019; Priority for Reducing Fuel Consumption and Emission. *IEEE Systems Journal*, PP(99), 1–9. <https://doi.org/10.1109/JSYST.2015.2500587>
- Suzumura, T., McArdle, G., & Kanezashi, H. (2015). A high performance multi-modal traffic simulation platform and its case study with the Dublin city. In *2015 Winter Simulation Conference (WSC)* (pp. 767–778). <https://doi.org/10.1109/WSC.2015.7408214>
- Tubaishat, M., Qi, Q., Shang, Y., & Shi, H. (2008). Wireless Sensor-Based Traffic Light Control. In *2008 5th IEEE Consumer Communications and Networking Conference* (pp. 702–706). <https://doi.org/10.1109/ccnc08.2007.161>
- Tubaishat, M., Shang, Y., & Shi, H. (2007). Adaptive Traffic Light Control with Wireless Sensor Networks. In *2007 4th IEEE Consumer Communications and Networking Conference* (pp. 187–191). <https://doi.org/10.1109/CCNC.2007.44>
- Wen, W. (2008). A dynamic and automatic traffic light control expert system for solving the road congestion problem. *Expert Systems with Applications*, 34(4), 2370–2381. <https://doi.org/10.1016/j.eswa.2007.03.007>

- Wongpiromsarn, T., Uthaicharoenpong, T., Wang, Y., Frazzoli, E., & Wang, D. (2012). Distributed traffic signal control for maximum network throughput. In *2012 15th International IEEE Conference on Intelligent Transportation Systems* (pp. 588–595). <https://doi.org/10.1109/ITSC.2012.6338817>
- Xiao, Z., Xiao, Z., Wang, D., & Li, X. (2015). An intelligent traffic light control approach for reducing vehicles CO₂ emissions in VANET. In *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)* (pp. 2070–2075). <https://doi.org/10.1109/FSKD.2015.7382270>
- Younes, M. B., & Boukerche, A. (2016). Intelligent Traffic Light Controlling Algorithms Using Vehicular Networks. *IEEE Transactions on Vehicular Technology*, 65(8), 5887–5899. <https://doi.org/10.1109/TVT.2015.2472367>
- Younes, M. B., Boukerche, A., & Mammeri, A. (2016). Context-aware traffic light self-scheduling algorithm for intelligent transportation systems. In *2016 IEEE Wireless Communications and Networking Conference* (pp. 1–6). <https://doi.org/10.1109/WCNC.2016.7564924>
- Younis, O., & Moayeri, N. (2016). Cyber-physical systems: A framework for dynamic traffic light control at road intersections. In *2016 IEEE Wireless Communications and Networking Conference* (pp. 1–6). <https://doi.org/10.1109/WCNC.2016.7564921>
- Yu, D., Wu, Y., & Yang, N. (2016). Research on Area Control Method in Urban Signal Intersection under the Multi - agent System. In *2016 Eighth International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)* (pp. 502–509). <https://doi.org/10.1109/ICMTMA.2016.126>
- Zhang, Y., Su, R., & Gao, K. (2015). Urban road traffic light real-time scheduling. In *2015 54th IEEE Conference on Decision and Control (CDC)* (pp. 2810–2815). <https://doi.org/10.1109/CDC.2015.7402642>
- Zhou, B., Cao, J., Zeng, X., & Wu, H. (2010). Adaptive Traffic Light Control in Wireless Sensor Network-Based Intelligent Transportation System. In *Vehicular Technology Conference Fall (VTC 2010-Fall), 2010 IEEE 72nd* (pp. 1–5). <https://doi.org/10.1109/VETECF.2010.5594435>
- Zhou, H., Bouyekhf, R., & EL Moudni, A. (2013). Concept of Transportation Entropy and Its Application in Traffic Signal Control. *IFAC Proceedings Volumes*, 46(25), 37–42. <https://doi.org/10.3182/20130916-2-TR-4042.00002>